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INCLUDING MAXIMUM SUSTAINED
WIND SPEED IN A TIME SERIES MODEL
TO FORECAST HURRICANE MOVEMENT

THESIS

Timothy B. Mott, Captain, USAF

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THESIS

Presented to the Faculty of the School of Engineering

of the Air Force Institute of Technology

Air University

In Partial Fulfillment of the

Requirements for the Degree of

Master of Science in Operations Research

Timothy B. Mott, B.S.

Captain, USAF

March 1993

Preface

The purpose of this research was to modify Dr. Thomas F. Curry's time series model for predicting hurricane landfall by including maximum sustained wind speed as an explanatory variable. The focus of this research was on improving the forecasting ability of Curry's model on the storms in the period 1945-1989.

In performing the analysis, writing the computer code, and compiling this thesis, I have had a great deal of help from certain specific individuals. First, I am very thankful to Dr. Edward F. Mykytka for his assistance and for deciding to advise this research, despite his initial reluctance. I am also grateful to Lt Col James T. Moore for giving this topic the initial support, and his pointed suggestions that kept me moving in the right direction. I am also indebted to Dr. Curry for his continuous assistance and guidance, and for sparking my interest in this topic. Thanks are also added to Mr. Colin McAdie of the National Hurricane Center for procuring data and answering questions during the height of the 1992 hurricane season. Special thanks goes to Capt Randy McCanne and Capt Bob Faneuff for their words of encouragement and alleviating humor.

Finally, the most important contributor is my fiancee, Laura McCreery, who kept my spirits high and my perspective in line, allowing me to complete the thesis.

<div align="right">T. B. M.</div>

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Abstract

Techniques for applying time series fundamentals to forecasting hurricane movement are thoroughly examined in this research The objectives are· (1) to modify Dr. Thomas Curry's threshold autoregressive time series model to improve its ability to forecast hurricane movement, (2) to forecast the maximum sustained wind speed for a hurricane, and (3) to identify if wind speed should be included as an explanatory variable to aid in forecasting hurricane movement.

Eleven different models to predict the latitude, longitude and maximum sustained wind speed are compared and contrasted with Curry's bivariate time series model. The results showed the modifications allow significant forecasting improvement to Curry's model in the 6-, 12-, 24-, 48- and 72-hour forecasts. The model recommended by this research shows a significant improvement in mean and variance of the overall forecast errors.

One of the emerging interests of the hurricane forecasting community is the ability to predict the intensity of a storm. An added feature of the recommended model is that it would predict the maximum sustained wind speed of the 72-hour forecast with mean error of less than 4 miles per hour. This makes the recommended model even more valuable to the hurricane forecaster.

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I. Hurricane Forecasting

This research will focus on predicting hurricane movement using a mathematical model, specifically a time series model. Models such as this can aid the hurricane forecaster in predicting where a hurricane may hit a coastline.

Andrew and Hugo; two hurricanes that hit the United States coastline in the last few years caused billions of dollars in damages and many deaths. It is an occurrence that is all too familiar, especially for people living in the areas that are in most danger. They know that when a hurricane is headed their way, it is time to board up the house and prepare to evacuate. The more warning time they have, the better chance they have to save their lives and protect their property. They need an accurate forecast of where the hurricane is going to strike.

For example, as hurricane Hugo approached South Carolina, authorities never expected the hurricane to hit the coast as soon as it actually did, which prevented timely evacuation. In all, Hugo took 85 lives and caused tremendous amounts of damages. (16:A2) It is possible that some of these lives could have been spared with more time to evacuate.

In the Florida Keys, a timely forecast of an approaching hurricane means the difference between survival and loss. Authorities determine that because of the one road system that connects the keys to the mainland, it would take "at least 30 hours to clear the area." (16:A2)

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1.1 Hurricane Forecast Models

Tremendous amounts of research have gone into the prediction of where a hurricane will hit land with little improvement over the last thirty years despite advancements in computers and weather monitoring devices. The majority of forecasting models use meteorological information to predict how a storm will steer. Others use simulation and statistical information to get a best guess of a storm's path.

The major United States agency involved in hurricane movement is the National Hurricane Center (NHC) in Coral Gables, Florida. While tracking an active hurricane, the NHC issues forecasts at least every 6 hours and predicts storm movement for lead times up to 72 hours (4:3). They use several computer models to analyze storm movement (11:522). The experienced and skilled forecaster would combine the output of these models with other accumulated data and "using his best judgement issue a forecast" (4:5-6). Still many feel that the hurricane forecasts are not timely enough or accurate enough to guarantee the safe evacuation of large, densely populated areas. In fact "after 30 years of advances in weather satellites, computer forecasting models, and basic research, forecasters had reduced the errors in predicting the paths of hurricanes by just 14%" (7:917). This is not encouraging when facing the destructive capabilities of a hurricane like Andrew.

1.2 Hurricane Forecasting with Time Series Models

Dr. Thomas Curry, who has done some of the most recent work in improving current forecasting procedures, feels that "the crux of the problem rests with the inadequacy of the present forecasting procedures" (4:2). He goes on to explain that in 1985 the National Hurricane Center (NHC) was using forecasting packages and computer systems which were thought to be

outdated and slow. Their 72-hour forecasts generally took two to three hours to develop with an average forecast error of 435 nautical miles. This error leaves populated areas with the costly decision to either evacuate or take the chance that the hurricane will miss their area. Greater accuracy is required in predicting hurricane landfall in order to insure timely evacuation.

Through the use of a nonlinear time series forecasting model, Dr. Curry was able to show that the landfall of certain types of hurricanes and tropical storms "can be accurately predicted by modeling the storm track as a bivariate (latitude and longitude) fifth-order autoregressive process" (4:v). His model produced forecasts which were slightly better than the NHC's official forecast.

The objectives of this research are: (1) to modify Curry's threshold autoregressive time series model to improve its ability to forecast all types of hurricanes, (2) to forecast the maximum sustained wind speed for a hurricane, and (3) to include past maximum sustained wind speeds as a explanatory variables to aid in forecasting hurricane movement.

II. Theoretical Development and Application

Predicting the movement of a hurricane is a difficult assignment. Nature does not assist the forecaster by following a set of rules or timetables. Thus, it is up to the forecaster to use the information available to best predict the destructive path of a hurricane.

Curry stated that Dr. William G. Lesso and T. W. Freeze determined that through the use of past hurricane tracks, some information can be extracted to aid in predicting hurricane movement (4:11). The Lesso and Freeze model uses only the current position report to forecast the future movement of a hurricane. Curry expanded this work in two ways: (1) incorporating a time series model which allows past position reports to be used in developing a forecast and (2) allowing the model parameters to vary over location, in order to more accurately model the distinctive, position-dependent motion of a hurricane.

This chapter describes the different types of time series models and how they apply to forecasting hurricane movement. The following areas will be covered:

- Univariate Autoregressive Moving Average (ARMA) Models

- Multivariate Autoregressive Moving Average (MARMA) Models

- Threshold AR Models

- Combining Cross-Sectional and Time Series Data

- Summary of Curry's Methodology

- Research Limitations

In the process of developing these areas, Curry's work will be developed in context and a number of possible time series models will be proposed for forecasting hurricane movement.

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2.1 Univariate Autoregressive and Moving Average (ARMA) Models

Time series modeling assumes that history repeats itself and its methods aim at discovering the past (historical) pattern of events so they can be extrapolated to forecast the future (8:363). Time series forecasting techniques are used to predict future values of a set of ordered observations where the order of the observation is as crucial as the observation itself (9:30). In other words, information from a time series would be lost if the observations were taken out of the order in which they were observed. The standard notation for a time series will be used in this research, in which the time order of an observation is conventionally denoted by a subscript. Accordingly, the general observation is written as Y_t, meaning the tth observation of a time series. This implies that the preceding observation is Y_{t-1} and the subsequent observation is Y_{t+1}. (9:30)

Time series models are used to express forecasts as functions of past values of the time series. The goal in time series forecasting is to find the function that best describes the nature of the observations. One approach to modeling time series is called the Autoregressive Moving Average (ARMA) models. An ARMA model represents the observation at time t as a function of previous observations and a random shock, e_t. In an ARMA model, the series of random shocks is assumed to be "white noise," which has the statistical property of being distributed Normally and independently with a zero mean and constant variance.

The first part of an ARMA model is the autoregressive (AR) process; the general equation, that best defines an AR process of order p, denoted AR(p), is:

$$Y_t = C + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + e_t \qquad (1)$$

where C is a constant and ϕ_i is the parameter which describes the weight given to the ith previous

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observation for i = 1,...,p. The AR process indicates that future expected values are linear combinations of p past values. That is, in an AR process of order p, the expected observation at time t, $E(Y_t)$, is a linear combination of the p previous observations, $Y_{t-1},...,Y_{t-p}$. The order of an AR model is dependent upon the nature of the process being modeled. Specifying a suitable order of an AR model and thus which past values should be utilized is crucial for obtaining accurate forecasts. In this research, *determining the order of the model* will refer to the specification of AR models.

The second part of an ARMA model is the Moving Average (MA) process which is characterized by a finite persistence (9:61). MA models are different from AR models as they assume that the expected observation at time t, $E(Y_t)$, is a linear combination of the previous model errors, $e_{t-1}, ...,e_{t-q}$. The general model equation for a MA process of order q, denoted MA(q), is:

$$y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_{q-1} e_{t-q-1} - \theta_q e_{t-q} \qquad (2)$$

where θ_i is the parameter which describes the weight given to the error of the ith previous model error for i = 1,...,q.

An ARMA model is a mix of the autoregressive and the moving average models. The general form of an ARMA model, of order (p,q), is:

$$y_t = C + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q} \qquad (3)$$

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Makridakis points out that the "advantage of an ARMA scheme is that it includes different AR models and uses whatever error remains in an MA equation in attempting to further improve forecasting." (8:229) An ARMA model will allow more capability in reducing the model errors to randomness than either AR or MA models alone.

Choosing the appropriate order (p,q) of the ARMA model can be difficult since there is no well-defined selection criteria. This can be overcome by following the guidelines of the Box-Jenkins methodology, which help make ARMA models relevant and applicable in real life situations (8:230).

Next, this methodology will be summarized briefly, then three important topics relevant to this research will be addressed: (1) model specification, (2) stationarity and (3) predicting hurricane movement with a univariate ARMA model.

2.1.1 *Box-Jenkins Methodology* The first step in the Box-Jenkins method is to postulate an order for an initial ARMA model. It is possible to identify a tentative ARMA model by examining the autocorrelation function of the time series, which measures the strength of the relationship between observations in the series that are the same number of time lags apart, and its partial autocorrelation function, which shows the relative strength of the relationship that exists for varying time lags (8:24,). Once the model has been postulated, the next step is to estimate the parameters of this tentative model. This is done with standard estimation methods such as maximum likelihood estimation or least squares estimation. After the model parameters have been estimated, the residual differences between the observed time series values and those estimated by the model should appear to be white noise for the fitted model to be "adequate". This can be determined by examining the autocorrelation function of the residuals. If the

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residuals do appear to be white noise, then the model is considered adequate. Otherwise, one must return to the model identification stage, select a different order for the model and step through the procedures again (8:245-250). Once the model has been shown to be adequate, the analyst should then look for redundant parameters. Finally, once these are eliminated, the resulting model can be used for forecasting purposes.

In his dissertation, Curry discusses ARMA models but limits his methodology to autoregressive models only. He implicitly incorporates possible moving average components by noting that moving average models can be approximated by truncated finite AR models. This decision is necessitated by the small number of observations within a hurricane track, since these short tracks make the MA parameters difficult to estimate. Consequently, Curry suggests that inclusion of an MA parameter is more complicating than helpful. Since we concur with his assessment, only autoregressive models will be addressed from this point on.

2.1.2 *Model Specification* As in regression analysis, one concern in time series model-building is specifying the order of the model, or determining which explanatory variables (i.e., previous observations) ought to appear in the model and which ones should not. Pindyck and Rubinfeld explain that there are trade-offs which are encountered in determining the explanatory variables. Their analysis shows that the cost of excluding a variable which should appear in the model is bias and inconsistency, while the cost of adding one or more irrelevant variables is loss of efficiency. They also point out that with a large number of observations, the loss of degrees of freedom in adding irrelevant variables is unlikely to be serious. The analyst must decide what is important in terms of the bias-efficiency tradeoff, with the result dependent upon the objectives of the analysis.

An initial estimate of a model's appropriateness can be obtained by examining the amount of variance in the observed time series that is explained by the model. Two of the common measures of this are the mean squared error (MSE) and the coefficient of multiple determination (R^2). MSE measures the error that is not explained by the model; it is calculated by:

$$MSE = \frac{\sum_{i=1}^{n} (Y_i - Yf_i)^2}{n-b} \qquad (4)$$

where n is the number of observations for which forecasts are developed using the model, Y_i is the actual i^{th} observation, Yf_i is the forecast of the ith observation and b is the number of dependent variables in the model. Minimizing the MSE appears to be one reasonable objective to determine model appropriateness since it accounts for both bias and efficiency (15:131). R^2 measures the proportionate reduction of the total variation in the dependent variable associated with the use of the particular set of dependent variables; it is calculated by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - Yf_i)^2}{\sum_{i=1}^{n} (Y_i - \overline{Y})} \qquad (5)$$

$$\overline{Y} = \sum_{i=1}^{n} \frac{Y_i}{n}.$$

The higher the R^2 value the more variance is explained by the model. These two measurements give a good idea of the appropriateness of the model. Both MSE and R^2 are usually computed in relation to the set of observations in developing estimates of the model's parameters.

In the case of comparing different forecasting models, the model that does the best job forecasting the observations within a separate test set should be the one chosen. One procedure

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to compare forecasting models is to compare the average and standard deviation of the forecast errors when forecasting on the test set. In addition, a more accurate way of measuring actual predictive capability of a model is to use the model to predict each observation in the test set and then to calculate the mean of the squared prediction errors, to be denoted by MSPR:

$$MSPR = \frac{\sum_{i=1}^{n} (Y_i - Yf_i)^2}{n} \tag{6}$$

where n is the number of forecasts, Y_i is the actual i^{th} observation and Yf_i is the forecast of the ith observation. The MSPR gives a good indication of how well the selected regression model will predict in the future, since it increases more rapidly than the mean error when many large errors are present. In the case of multiple models exhibiting statistically equivalent results, meaning the forecast error average, standard deviation and MSPR of the models are equivalent to some desired confidence level, the model with the minimum number of terms would be the one of choice.

2.1.3 *Stationarity* In developing models for time series, it is important to know whether or not the underlying stochastic process that generated the series can be assumed to be invariant over time. In particular, we usually assume that this means the series mean, variance and autocorrelation structure do not change over time. If the mean or variance changes over time (i.e., is nonstationary),

> it will often be difficult to represent the time series over past and future intervals of time by a simple algebraic model. On the other hand, if the process is fixed in time (i.e., is stationary), then it is possible to model the process via an equation with fixed coefficients (linear in coefficients) that can be estimated from past data. (15:497)

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Thus, to accurately estimate parameters for an ARMA model, the time series must be stationary. Otherwise, the ability to accurately forecast future observations could be drastically diminished.

A time series which is nonstationary in the mean can sometimes be transformed into a stationary series if it is differenced one or more times. Differencing is subtracting the value of the previous observation from the current (time t) observation, and doing this for every observation in the time series, i.e. forming for t = 2, 3, ..., n:

$$w_t = y_t - y_{t-1} = \Delta y_t. \tag{7}$$

Thus if we want to build a time series model to forecast values for a nonstationary (in the mean) series, we can (hopefully) difference the series until stationary, construct a model for this differenced series, make forecasts for this series, and then remove the effect of the differencing in the model and its forecasts to develop forecasts for the original series.

Unfortunately, even if a series is stationary in its mean, it may not be stationary in its variance. In practice, most time series can be made stationary in mean and variance by differencing, but when this is not the case, there is another simple transformation which may be applied to such processes to make them stationary in the larger sense. "In general, whenever the variance of a time series changes as the level of the series changes, the series can be made stationary in the larger sense (in both mean and variance) by log-transformation and then differencing. Log-transformation and differencing results in a constant variance." (9:52) In conclusion, a series which is not stationary in its mean and/or variance may lead to incorrect inferences in the analysis.

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2.1.4 *Hurricane Forecasting Using Univariate ARMA Models*   In forecasting

hurricane movement, univariate AR models could be used in forecasting latitude and longitude

coordinates separately, although these would not account for any dependence between them.

(Curry assumed there was a significant dependence between latitude and longitude and, therefore,

fit bivariate models only.) It may be beneficial to fit two separate univariate models for latitude

and longitude to use as a basis for comparison with other, more complicated, models. These

univariate models would have the form:

$$LA_t = \phi_{1,1}LA_{t-1} + \phi_{1,2}LA_{t-2} + \ldots + \phi_{1,p}LA_{t-p} + e_{1t} \qquad (8)$$

$$LO_t = \phi_{2,1}LO_{t-1} + \phi_{2,2}LO_{t-2} + \ldots + \phi_{2,p}LO_{t-p} + e_{2t} \qquad (9)$$

where LA_t and LO_t are the latitude and longitude at time t, the e's are the model errors, and the

ϕ's are appropriate AR model parameters.

2.2 Multivariate ARMA (MARMA) Models

MARMA models are used to apply time series methods where additional variables are to

be included in a model to provide additional information to be used in developing a forecast.

There are two reasons for analyzing and modeling multiple series jointly: (1) to understand the

dynamic relationships among them and (2) to improve accuracy of forecasts, since, when there

is information on one series contained in the historical data of another, better forecasts can result

(21:802). Next, two types of MARMA models that are referred to in the literature will be

distinguished: vector ARMA models and a subset of vector ARMA models identified as transfer

function models.

2.2.1 *Vector ARMA Models* This useful class of models allows for the application of time series methods to jointly forecast multiple time series using the past history of these series as predictors. Vector ARMA models allow feedback relationships among the multiple series, where the forecasts of a series can depend on the forecasts of other series. The parameter estimation techniques for vector ARMA models can be quite complex, particularly with the hurricane track data used in this research. Accordingly, only the subset of vector ARMA models called transfer functions were utilized in this research.

2.2.2 *Transfer Function Models* Transfer function models are a unique variation of vector ARMA models in which time series methods are applied to forecast a single dependent series with additional series included as predictors. The general transfer function model may be written as

$$Y_t = \delta_1 Y_{t-1} + \delta_2 Y_{t-2} + \ldots + \delta_r Y_{t-r} + \omega_0 X_{t-b} - \omega_1 X_{t-b-1} - \ldots - \omega_s X_{t-b-s}$$
$$+ \zeta_0 Z_{t-c} - \zeta_1 Z_{t-c-1} - \ldots - \zeta_m Z_{t-c-m}$$
$$+ .$$
$$+ . \qquad\qquad (10)$$
$$+ .$$
$$+ \xi_0 W_{t-d} - \xi_1 W_{t-d-1} - \ldots - \xi_v W_{t-d-v}$$
$$+ e_t$$

where Y_t is the dependent variable, and X, Z, and W are the independent variables. If b, c and d are greater than zero, the corresponding independent variables (X, Z or W) will be leading indicators of Y_t. The purpose of transfer function methodology is to facilitate determination of r, s, b, c, m, d and v and the estimation of the parameter values.

When suitably arranged, a transfer function model possesses at best, a *triangular* relationship which allows for partial feedback between responses. Box and Tiao describe this *triangular* relationship in an example in which "Y depends only on its own past; X_1 depends only

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on its own past and on the present and past of Y; X_2 depends on its own past and on the present and past of Y and X_1; and so on." (21:802)   This means that when there is a feedback relationship between the variables such that, Y depends on the past of X_1 and X_1 depends on the past of Y, a transfer function cannot account for the feedback; however, another type of vector ARMA model could.

Curry wanted to account for a dependence between latitude and longitude, but he felt a feedback relationship was not necessary. In other words, he did not use predicted values of latitude or longitude as predictor variables for each other.   Instead, he accounted for this dependence by using two separate transfer functions; one for latitude and one for longitude. Curry's basic models express latitude at time t (LA_t) as a function of past latitude and longitude reports, and longitude at time t (LO_t) as a function of past longitude and latitude reports as well:

$$
\begin{aligned}
LA_t = & \phi_{11,1}LA_{t-1} + \phi_{11,2}LA_{t-2} + \ldots + \phi_{11,p}LA_{t-p} \\
& + \phi_{12,1}LO_{t-1} + \phi_{12,2}LO_{t-2} + \ldots + \phi_{12,r}LO_{t-r} \\
& + C_1
\end{aligned}
\tag{11}
$$

$$
\begin{aligned}
LO_t = & \phi_{21,1}LA_{t-1} + \phi_{21,2}LA_{t-2} + \ldots + \phi_{21,p}LA_{t-p} \\
& + \phi_{22,1}LO_{t-1} + \phi_{22,2}LO_{t-2} + \ldots + \phi_{22,r}LO_{t-r} \\
& + C_2
\end{aligned}
\tag{12}
$$

where C_1 and C_2 are constants and the ϕ's are the model parameters.

According to Curry, this model can be expressed as a multivariate linear model wherein the ϕ's can be estimated via multivariate least squares (4:63-64). He goes on to state that "although they are biased, the least square parameter estimates converge in probability to the true parameter values." (4:64) A variation to Curry's model would include wind speed (WS) as a predictor while keeping both latitude and longitude in the model. This model would be:

$$LA_t = \phi_{11,1}LA_{t-1} + \phi_{11,2}LA_{t-2} + \ldots + \phi_{11,p}LA_{t-p}$$
$$+ \phi_{12,1}LO_{t-1} + \phi_{12,2}LO_{t-2} + \ldots + \phi_{12,q}LO_{t-q} \qquad (13)$$
$$+ \phi_{13,1}WS_{t-1} + \phi_{13,2}WS_{t-2} + \ldots + \phi_{13,r}WS_{t-r}$$
$$+ C_1$$

$$LO_t = \phi_{21,1}LA_{t-1} + \phi_{21,2}LA_{t-2} + \ldots + \phi_{21,p}LA_{t-p}$$
$$+ \phi_{22,1}LO_{t-1} + \phi_{22,2}LO_{t-2} + \ldots + \phi_{22,q}LO_{t-q} \qquad (14)$$
$$+ \phi_{23,1}WS_{t-1} + \phi_{23,2}WS_{t-2} + \ldots + \phi_{23,r}WS_{t-r}$$
$$+ C_2$$

$$WS_t = \phi_{31,1}LA_{t-1} + \phi_{31,2}LA_{t-2} + \ldots + \phi_{31,p}LA_{t-p}$$
$$+ \phi_{32,1}LO_{t-1} + \phi_{32,2}LO_{t-2} + \ldots + \phi_{32,q}LO_{t-q} \qquad (15)$$
$$+ \phi_{33,1}WS_{t-1} + \phi_{33,2}WS_{t-2} + \ldots + \phi_{33,r}WS_{t-r}$$
$$+ C_3$$

where LA_t represents the latitude at time t, LO_t represents the longitude at time t, WS_t represents the maximum sustained wind speed at time t and C_1, C_2 and C_3 are constants.

Wind speed would be added based on the advice of both Curry (4:109) and Pike (14:101), a research meteorologist from the National Hurricane Center. Pike states that "preliminary tests confirm that the winds are superior to heights (atmospheric pressures at different altitudes traditionally used in predicting tropical storm steering) as steering predictors (of tropical storms)." (14:103) It is expected that the inclusion of maximum wind speed as an explanatory variable will decrease forecast error. Maximum wind speed is used in order to keep the forecasting models as simple as possible since it was decided that other measures of a hurricanes winds, including its "wind component vectors" (3) would be rather complicated to incorporate into a model and would also be cumbersome to use.

Unfortunately, there are two unique complicating factors that do not allow these types of models to be simply estimated or fit. First, the set of historical time series of hurricane track

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data which will be used to fit a model is not a single continuous time series but rather is a collection of multiple time series (i.e., separate hurricane tracks) referred to as cross-sectional time series. As will be seen, this complicates procedures for estimating the parameters for the models. Second, to overcome possible large errors in predicting hurricane movement, Curry allowed his model coefficients to change as a storm moves. This is done by estimating the nonlinear motion by a number of linear estimates within the context of a threshold AR model. These complications will be addressed in the next two sections.

2.3 Threshold AR Models

The movement of hurricanes is not by nature a random phenomenon, but rather, hurricanes "tend to be steered by the large atmospheric forces in which they are embedded." (11:352) This steering can be seen in Figure 2.1, which shows four typical hurricane tracks over the North Atlantic basin. Notice that the storms tend to move first to the west and north, and then turn more to the north and east as they move progressively northward. Curry developed his model so that the model parameters could change as the storm moved northward in order to account for this type of movement. He accomplished this by using a threshold AR model.
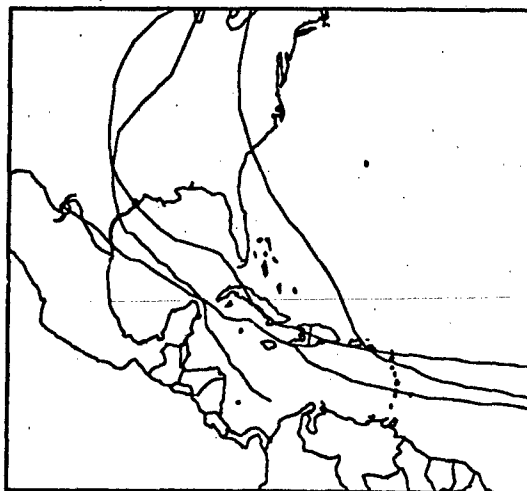
Figure 2.1. Four Typical Hurricane Tracks Over the North Atlantic Basin.

A threshold AR model is basically a piecewise linearization of a nonlinear process. It accounts for the motion of the hurricane by

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allowing the parameters to change as the storm crosses latitude thresholds. This allows the

forecast parameters to remain constant until the next threshold is crossed, since the nature of the

storms is believed to change slowly (4:23). By "segmenting the North Atlantic into latitude

bands" (4:107), and estimating the parameters for the separate time series in each band, the

motion of a storm can be embodied by "piecing" together the models in the separate bands. The

latitude bands that Curry chose are: 10-15N, 15-20N, 20-25N, 25-30N, 30-35N, 35-40N and

40-45N in degrees latitude (see Figure 2.2). Accordingly, Curry develops seven separate and

unique models, one for each latitude band (4:113).

In this research, a threshold model will be constructed by taking all the position reports

for each storm which lie within a latitude band and estimating the AR parameters for the model
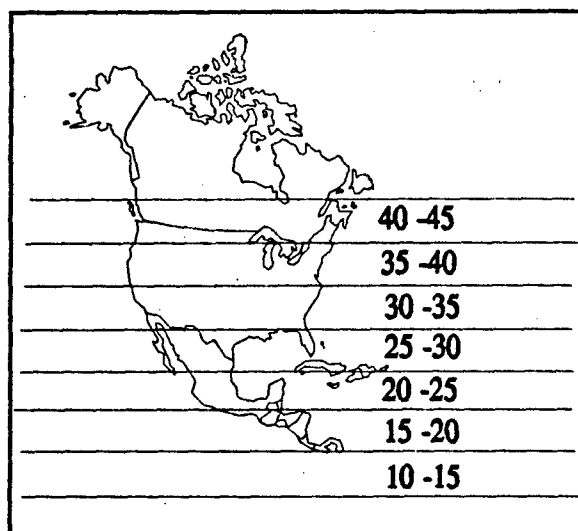
Figure 2.2. The Latitude Band for the Threshold AR Model.

within that band using only those observations and the five most previous position reports. Using the previous five position reports ensures that an AR model of order less than or equal to five would be appropriate to be used immediately once a storm crosses a threshold. If there was no overlap (i.e., if the five most previous position reports were not included), it would not be appropriate to develop forecasts immediately when a storm

moves into a new region. For example, using an AR(5) model constructed for that latitude band,

forecasts could not be developed until five position reports had been obtained in that band.

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Using a five position report overlap allows forecasts to be issued immediately when a storm moves into that region using the model constructed for that latitude band .

A threshold AR model forecast of a hurricane's next position (6 hours in the future) will thus be made by using the time series model for latitude band within which the most recent position report lies. Once this forecast is calculated, the next step ahead forecast (i.e., for 12 hours ahead) is made using the time series model for the latitude band in which the first forecast lies. This model will be the same as the one used for the first forecast unless the first forecast crossed a "threshold." Then, the model for the new latitude band would be used. This process is repeated until the required number of forecasts are obtained.

The threshold AR model thus allows for the AR parameters to change as the storm moves while still allowing the forecasts to be functions of the past values of the storm's positions. The evidence supporting the use of a threshold model as described by Curry seems reasonable and justified. Accordingly, this threshold approach will be utilized in this thesis with the same latitude bands.

2.4 Combining Cross-sectional and Time Series Data

In the normal application of time series analysis, there are a large number of time-ordered observations of the series of interest and, using these observations the goal is to explain and forecast the future values of that series. By examining the patterns, trends, or persistence of the past observations, information is gained on future values. However, the life of a particular hurricane is short, and the goal is to use the movement history of all past storms to predict the movement of a current storm. According to Pindyck and Rubinfeld,

a practical problem of some importance occurs when observations are available for several individual units (hurricanes) over a period of time. Occasionally sufficient observations will not be available to estimate either a time series (dealing with correlations between time periods) or cross-section (dealing with correlations between individual units) equation, suggesting that some method of combining the data (of individual hurricanes) be used. The process of combining cross-section and time series data is pooling. (15:252-253)

It seems appropriate to use information from past hurricane tracks to forecast a current hurricane's movements. Accordingly, we are not dealing with one long, continuous time series but, rather, with a collection of many smaller time series driven, we assume by a common underlying natural process; i.e., we assume hurricanes behave or move according to a common natural process.

The problem lies in having to combine the necessary information from many past hurricanes to forecast the movement of a single current hurricane, while also incorporating information about the present storm's history. One complication arises in estimating the model parameters, since many observations are needed to keep the variance of the parameter estimates small. While it seems obvious that this could be accomplished by combining the hurricane tracks "so as to maximize the number of observations" (4:60), it produces quite a unique problem. To illustrate this problem , we take two tracks, each with four observations:

$$Track_1 = [LA_{1,1}, LA_{1,2}, LA_{1,3}, LA_{1,4}] \qquad (16)$$

$$Track_2 = [LA_{2,1}, LA_{2,2}, LA_{2,3}, LA_{2,4}] \qquad (17)$$

If we combined the tracks by appending Track$_2$ at the end of Track$_1$, we would obtain

$$Combined \ [LA_{1,1}, LA_{1,2}, LA_{1,3}, LA_{1,4}, LA_{2,5}, LA_{2,6}, LA_{2,7}, LA_{2,8}] \qquad (18)$$

This would appear to yield a single track containing eight observations to work with. It would seem appropriate to fit a time series model to this set of eight observations via traditional time series methods. Unfortunately, this would not be suitable since the first four observations are independent from the last four because they arise from two different storms. Traditional methods would assume that the first four observations are related to the last four.

The method that Curry used to overcome this obstacle is to estimate the parameters using the SPSS multivariate linear regression procedure with "the pairwise deletion option" (4:60). This results in the covariance matrix having a different number of pairs for each off diagonal element, which in turn has a minor effect on the confidence interval for the associated coefficient.

There are few other published results relating to the estimation of AR parameters when dealing with pooled cross-section and time series data. Azzalini (1991) provides one exception as he develops a "nearly unbiased estimate of the AR(1) parameter" for dealing with pooled data in a time series (Azzalini:273). Azzalini's equation:

$$\tilde{\rho} = \frac{2\sum_{i}\sum_{t=2}^{T} (y_{i,t}-\mu_i)(y_{i,t-1}-\mu_i)}{\sum_{i}[\sum_{t=1}^{T}(y_{i,t}-\mu_i)^2 + \sum_{t=2}^{T-1}(y_{i,t}-\mu_i)^2]} \tag{19}$$

gives a good estimate of ρ, which can be used as the ϕ_1 estimate. Unfortunately, this is not appropriate for our situation for two reasons. First, it is only appropriate for an AR(1) process which we find restrictive. Secondly, Azzalini's equation assumes that each observed time series is of the same length. This is not the case for the hurricane data since each storm has a different number of position reports.

Another published technique is developed by Pindyck and Rubinfeld; it is a procedure called the "Time series Autocorrelation Model." They suggest "that one ought to consider pooling cross-section and times-series data under error assumptions involving time series autocorrelation (error terms from different time periods are correlated) as well as cross-section heteroscadisticity (constant error variance)." (15:258)

An example of how this might be accomplished using a latitude (LAT) model that uses wind speed (WS) as an explanatory variable is:

$$LA_{it} = \alpha + \beta WS_{it} + \varepsilon_{it} \qquad \varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + \upsilon_{it} \qquad (20)$$

where

$$E(\varepsilon_{it}^2) = \sigma^2$$
$$E(\varepsilon_{it}\varepsilon_{jt}) = 0 \qquad E(\varepsilon_{i,t-1}\upsilon_{jt}) = 0 \qquad i \neq j \qquad (21)$$
$$\upsilon_{it} \sim N(0, \sigma_\upsilon^2)$$

and the $i = \{i^{th}$ storm $i=1,...,N\}$ and $t = \{t^{th}$ time period, $t=2,...,T\}$.

The assumptions imply that cross-section disturbances (storms) are uncorrelated and have constant variance but time series disturbances are autocorrelated. We allow ρ to vary from individual unit to individual unit but fix each error structure to involve first-order serial correlation. We estimate each ρ_i (for each storm) and then use the estimated ρ_i as a basis for the generalized least-squares regression. To estimate ρ_i, $i = 1,2,...,N$, we estimate the entire pooled sample using ordinary least squares. Since the parameter estimates are consistent (as well as unbiased), we can use them to calculate the regression residuals ε_{it}. We then estimate each ρ_i consistently as follows:

$$\hat{\rho}_i = \frac{\sum_{t=2}^{T} \hat{\varepsilon}_{it}\hat{\varepsilon}_{i,t-1}}{\sum_{t=2}^{T} \hat{\varepsilon}_{i,t-1}^2} \qquad for \ i = 1,2,...,N \qquad (22)$$

We proceed by forming the generalized difference form of the original model:

$$
\begin{aligned}
LAT_{it} - \hat{\rho}_i LAT_{i,t-1} &= \alpha(1-\hat{\rho}_i) \\
&+ \beta(WS_{it} - \hat{\rho}_i WS_{i,t-1}) \\
&+ \varepsilon_{it} - \hat{\rho}_i \varepsilon_{i,t-1}
\end{aligned}
\tag{23}
$$

The generalized difference form can now be estimated by applying ordinary least squares to the pooled model. NT - N observations are used in the estimation, since one observation from each individual unit is dropped in the generalized differencing process. Corrections for heteroscedasticity or cross-section correlation between individual units would proceed in a fashion similar to that just described. If heteroscedasticity had been present in the model, for example, we would use the residuals of the generalized difference model (pooled) to estimate the individual error variances and then apply weighted least squares in the third stage of the estimation process. (15:258-259)

The cross-section explanatory variable could be thought of as the individual storms, where we could assume that the storms are independent of each other (uncorrelated) but that they have constant variances (velocity-stationary) but the time series disturbances (the movement over time) are autocorrelated. This technique will not be used in this research due to time constraints. Instead, we will adapt a variation of Curry's approach.

2.5 Review of Curry's Methodology

The objective of Curry's research focused on providing greater accuracy in predicting hurricane landfall in order to insure timely evacuation. His research focused on using a bivariate (latitude and longitude) fifth-order autoregressive model that could be used to predict the movement of a hurricane. He used a threshold approach to allow the model parameters to change as the storm moves to a new region of the ocean. This section will review Curry's data manipulation, model identification, parameter estimation, forecasting techniques, and model validation.

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2.5.1 *Data Manipulation* Curry used the "best track" storm data from the National

Environmental Satellite Data Information Service that contained position reports of subtropical

storms, tropical storms and hurricanes from 1886 to 1983 (4:131). Curry initially deleted all

storms that occurred before 1945 due to concerns about the accuracy of the observations (4:134).

Next, he limited his data to only the storms that occurred in the Northern Atlantic Basin because

this is the United States coastal region of concern. Then, all storms that did not attain more than

subtropical status (maximum wind less than 45 knots) were eliminated (4:40).

Curry then divided the hurricane data into seven latitude bands. Each band would cover

position reports with latitudes within a five degree interval. The latitude bands are: 10-15N, 15-

20N, 20-25N, 25-30N, 30-35N, 35-40N and 40-45N in degrees latitude.

After getting the data into workable sets, Curry's next step involved determining the

stationarity of the storms. Determining the "hurricane stationarity" of each storm was key to

Curry's research. He states that in order to develop models of the latitude series and the

longitude series, it was necessary to develop a procedure to determine if the series were weakly

stationary (4:30). He explains that,

> While it would seem that a hurricane which is continually in motion could never
> be considered to be stationary, this is not typically the case. If a storm is moving
> due west (W) or east (E), the latitude series remains constant. In this case the
> hurricane is latitude-stationary, i.e. the time series LA_{t-1}, LA_{t-2}, ..., LA_{t-n} varies
> about a constant mean. A storm moving due north (N) or south (S), is longitude-
> position stationary.
>   If the storm is moving northwest (NW), northeast (NE), southwest (SW),
> or southeast (SE), it is neither latitude-position stationary nor longitude position
> stationary. When this occurs, stationarity can be induced by differencing
> (calculating the change per unit time interval) the latitude and longitude series.
> If the new series (which now represents velocities) vary about a constant mean,
> the hurricane is said to be latitude-velocity and/or longitude-velocity stationary.
> It describes a storm moving (say NW) at constant velocity and is used to predict
> the next velocity, i.e. the next change in position. ... If the hurricane is

accelerating (say in latitude), the latitude series must be differenced twice to induce stationarity. The process of determining whether the latitude and longitude series are stationary in position, velocity, or acceleration, results in nine possible classifications for a particular track (see Table 2.1). (4:35-36)

Table 2.1. Curry's Hurricane Stationarity Classifications.

LATITUDE	LONGITUDE		
	POSITION	VELOCITY	ACCELERATION
POSITION	1. Standing Still	2. Moving East or West	3. Accelerating West or East
VELOCITY	4. Moving North or South	5. Moving NE, SE, SW, or NW	6. Recurving N,S or E,W
ACCELERATING	7. Accelerating North or South	8. Recurving W,E to N,S	9. Accelerating NE, SE, SW, or NW

Curry used an ad-hoc procedure in each latitude band to determine the stationarity classification of each storm. In this procedure, he calculated the latitude lag-one least squares regression coefficient and, if it was less than 0.8, the storm was considered latitude position-stationary If the coefficient was greater than or equal to 0.8, the lag-one latitude series was differenced, and a similar coefficient calculated for the differenced series. Then, if this coefficient was less than 0.8, the storm was considered latitude velocity-stationary. If still greater than 0.8, it was differenced a second time and another similar coefficient was calculated. Once again, if this was less than 0.8, the storm was considered latitude acceleration-stationary. If not, the storm was discarded. The procedure was repeated for longitude in each latitude band. The data matrices were then constructed for the stationarity class 5 storms. There was one data

matrix for each latitude band with the rows made up of one differenced observation and its first four lagged differences.

Curry developed forecast models for only the stationarity class 5 storms. First, this class contained the greatest number of observations in all the latitude bands. Second, it was found that no matter what stationary class the storm was in at the present, it was most frequently in stationarity class 5 at later positions. This implied that any acceleration or lack of any movement was short lived. "Consc quently, for six hour data a good guess of future stationary class of any hurricane would be lat tude-velocity, longitude-velocity stationary (class 5)." (4:98)

2.5.2 *Model Identification* Curry's next step was to identify the appropriate order for the autoregressive process. He determined that it was necessary to use the latitude and longitude velocities to make the time series stationary. By using the lag zero latitude and longitude velocity columns as dependent variables and the lags one through five latitude and longitude velocity columns as independent variables, he used a least squares regression procedure in SPSS to estimate the AR coefficients. This was used, instead of using a time series AR estimation package, because of the segmenting of the hurricane tracks.

Using the least squares regression procedure to estimate the parameters, he found significant (significantly different from zero) coefficients at lags 1, 4, and 5. He felt the significant lag 4 coefficient might imply "that the process could be autoregressive with a 'cyclic' component at lag 4, representing a 24 hour lag. This component could physically reflect the diurnal effect of the sun (the slowing of the storm at night)." (4:39) He then regressed only using lags 1, 4 and 5, and found that the lag 5 coefficient was "weak, so it was dropped from the model.

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This led to the general model with velocity coefficients evaluated at lags 1 and 4" (4:39), as follows:

$$
\begin{aligned}
LA_t - LA_{t-1} = &\ \phi_{11,1}(LA_{t-1} - LA_{t-2}) + \phi_{11,2}(LA_{t-4} - LA_{t-5}) \\
&+ \phi_{12,1}(LO_{t-1} - LO_{t-2}) + \phi_{12,2}(LO_{t-4} - LO_{t-5}) \\
&+ C_1
\end{aligned}
\tag{24}
$$

$$
\begin{aligned}
LO_t - LO_{t-1} = &\ \phi_{21,1}(LA_{t-1} - LA_{t-2}) + \phi_{21,2}(LA_{t-4} - LA_{t-5}) \\
&+ \phi_{22,1}(LO_{t-1} - LO_{t-2}) + \phi_{22,2}(LO_{t-4} - LO_{t-5}) \\
&+ C_2
\end{aligned}
\tag{25}
$$

where C and C_2 are constants and the ϕ's are the model parameters. Lagged terms past the sixth period were not considered due to the short tracks of individual hurricanes.

2.5.3 Parameter Estimation After deciding what order the general autoregressive model would have, the next step was to estimate its parameters. A separate forecast model was estimated for both latitude and longitude in each latitude band, making seven sets of latitude and longitude models. Curry estimated the parameters for each latitude band using least-squares regression, treating the lag-zero latitude and longitude velocities as the dependent variables and the lag-one and lag-four latitude and longitude velocities as the independent variables. He used SPSS regression procedures to calculate the parameter estimates (4:113-114).

2.5.4 Forecasting To predict the movement of hurricanes, Curry made six-hour forecasts of the last position report using the estimated latitude band models. The latitude of the last position of the storm dictated which latitude band model to use for the forecast. Once a six-hour forecast was made, it was used as the most current position report to make the next forecast. This was repeated until a 72-hour forecast was obtained. He furnished both point and interval forecasts for the hurricane's position.

2.5.5 Forecast Errors Curry's measured forecast error in terms of the great circle distance (in nautical miles) between the actual (LA,LO) and the forecasted (LA$_f$,LO$_f$) position of the eye of the hurricane. The great circle distance (GCD) is the standard measurement used in hurricane forecasting and is calculated by:

$$GCD = 60 \ arccos[\sin(LA_f)\sin(LA)+\cos(LA_f)\cos(LA)\cos(LO-LO_f)] \quad (26)$$

where all angles are in degrees. The statistics used for his error comparisons were the sample mean (MEAN) and the sample standard deviation (STD) of the forecast errors; computed via:

$$MEAN = \frac{\sum_{i=1}^{n} GCD_i}{n} \quad (27)$$

$$STD = \sqrt{\frac{\sum_{i=1}^{n} (GCD_i)^2 - n(MEAN)^2}{(n-1)}} \quad (28)$$

where n is the number of forecasted positions. MEAN gives an estimate of the expected forecast error, and the STD gives a measure for the dispersion of all values around the mean.

2.5.6 Model Validation Curry's final step was to validate his model. Curry had reservations about estimating error by forecasting the same storms that were used in estimating the model coefficients, so he deleted storms (one at a time) from the data base, recomputed the model coefficients, and he used these models to forecast the "deleted" storms. He concluded "that the large number of observations in each region tended to diminish the contribution of individual storms." (4:139) He decided that using the model building data set to validate his model was appropriate.

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2.6 Research Limitations

This research closely follows Curry's methodologies except in the following areas:

1. This research is focused on the modification of Curry's model to improve its ability to forecast <u>all</u> hurricanes, including storms which do not meet his hurricane velocity-stationarity classification. Thus, Curry's procedures for identifying velocity-stationary storms are not used.

2. This research will only concentrate on developing point forecasts of a hurricane's position. The interval forecasting procedures that Curry uses are not.

3. The same measurements for analyzing forecast error that Curry used will be used in this research with the addition of mean squared prediction error (MSPR), calculated by:

$$MSPR = \frac{\sum_{i=1}^{n} GCD_i^2}{n} \tag{29}$$

MSPR is the statistic of choice since it shows the effects of many large errors better than the mean or standard deviation.

III. Methodology

This chapter provides a discussion of the methodology used to examine each of the following areas in modifying Curry's model:

- Data Manipulation

- Model Building

- Forecasting

- Model Selection

3.1 Data Manipulation

The data files and the steps required to calculate the parameters for the time series models are described in this section. The areas covered are:

- Reduction of the Data

- Relaxation of Hurricane Stationarity

- Separation into the Latitude Bands

3.1.1 *Data Reduction* The storm data were provided via computer disk by Curry. The data set contained position reports at 6 hour intervals for storms, which includes hurricanes, tropical storms and subtropical storms, from the major basins worldwide dating from 1945 through 1989. The disk format had 28 characters per record, where each record was a 6 hour position report of a particular storm. The information in each record contained the storm identification number (ID), the date, the time, the latitude (LA), the longitude (LO) and the maximum sustained wind speed (WS) of the storm at the position report (see Appendix I).

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The initial data reduction step limited the scope of investigation to only the storms in the North Atlantic. Then, any storm that did not reach tropical storm status, which means its maximum sustained wind speeds did not exceed 45 knots, was "deleted because of their weak persistence." (4:134)

Based on the procedures that Curry used, the next step involved eliminating "position reports following landfall on the continental United States (US)." (4:134) This was done since the focus is to accurately predict hurricane landfall and the actual movement of a storm after landfall is inconsequential. This involved a slight complication, in that, the actual landfall of a storm was not included in the data files used for this research. In addition, because the US coastline is not a straight line or easily defined area and since hurricane landfall on the Florida peninsula can result in a second, crucial landfall on the Gulf Coast, an assumption was made in determining when a storm made landfall. This assumption involved drawing a "boundary of landfall" just inside the US
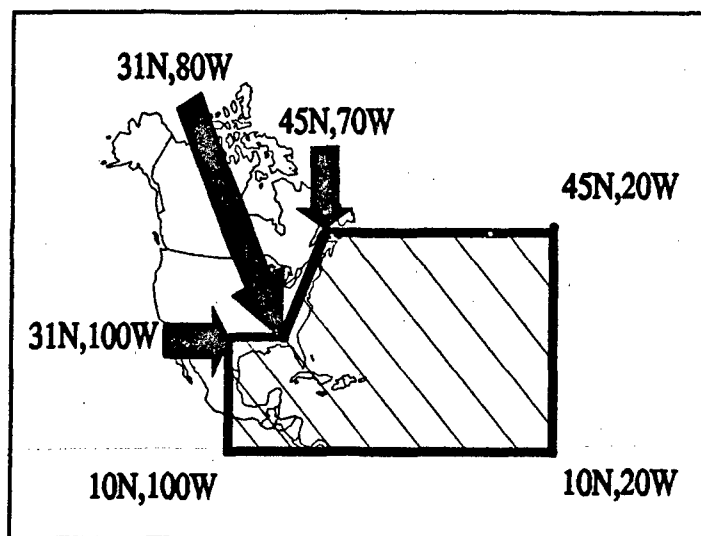
Figure 3.1. Landfall Cutoff Boundaries

coastline (see Figure 3.1). Any position reports that were past this boundary (inside the continental US) were considered after landfall and eliminated. The FORTRAN code used to set the boundary is included in Appendix H.

The final step involved establishing a set of test storms to be used in validating the models. The choice of this test set was based on the fact that Curry only used data through 1983 in fitting his models; accordingly we fit our models to the same data and included all storms that occurred after 1983 in the test data. There were 45 storms with over 1076 position reports in this test set dating from 1984 through 1989. After removing the test set, 351 storm tracks containing a total of 9508 position reports were left for estimating the parameters of the models.

3.1.2 *Relaxation of Hurricane Stationarity* It is important, in time series analysis, "to know whether or not the underlying stochastic (random) process that generated the series can be assumed to be invariant with respect to time." (15:497) If the series can be assumed to be invariant with respect to time, which means "the probability of a given fluctuation in the process from its mean level is assumed to be the same at any point in time ... it is possible to model the process via an equation with fixed coefficients that can be estimated from past data." (15:497). Thus parameter estimation for such a process takes much less effort than a nonstationary process. To account for stationarity in the hurricane series, Curry breaks the nature of a hurricane into nine stationarity classifications, as discussed in the previous chapter (see Table 2.1).

Although these stationarity classifications are logical, there is some question as to their relevance and also the practicality of determining the actual stationarity of a storm that is currently headed for the coast. First, when only using the storms that are classified as velocity-stationary in estimating model parameters, a lot of information is lost. The information contained in the storms not used because they were not velocity-stationary is wasted; thus for a current storm to be forecasted accurately, the storm must be velocity-stationary. This limits the application and the accuracy of the model.

This research will relax Curry's stationarity classes and use all the hurricane tracks to estimate model parameters in the latitude bands. It still, however, must be decided whether or not the time series of hurricane tracks are stationary or nonstationary. If the series are presumed to be nonstationary, the estimation procedures are complicated since the coefficients would have to be "time-varying" because the series is not "invariant with respect to time." Differencing would then appear to be required. On the other hand, if the series were presumed to be stationary, the overall structure of the model would be changed since differencing would no longer be required. Accordingly, the differenced model that Curry developed may not be the best available for forecasting. This suggests the following models with no differenced terms:

$$
\begin{aligned}
LA_t = &\ \phi_{11,1}LA_{t-1} + \phi_{11,2}LA_{t-2} + \ldots + \phi_{11,p}LA_{t-p} \\
&+ \phi_{12,1}LO_{t-1} + \phi_{12,2}LO_{t-2} + \ldots + \phi_{12,q}LO_{t-q} \\
&+ \phi_{13,1}WS_{t-1} + \phi_{13,2}WS_{t-2} + \ldots + \phi_{13,r}WS_{t-r} \\
&+ C_1
\end{aligned}
\tag{32}
$$

$$
\begin{aligned}
LO_t = &\ \phi_{21,1}LA_{t-1} + \phi_{21,2}LA_{t-2} + \ldots + \phi_{21,p}LA_{t-p} \\
&+ \phi_{22,1}LO_{t-1} + \phi_{22,2}LO_{t-2} + \ldots + \phi_{22,q}LO_{t-q} \\
&+ \phi_{23,1}WS_{t-1} + \phi_{23,2}WS_{t-2} + \ldots + \phi_{23,r}WS_{t-r} \\
&+ C_2
\end{aligned}
\tag{33}
$$

$$
\begin{aligned}
WS_t = &\ \phi_{31,1}LA_{t-1} + \phi_{31,2}LA_{t-2} + \ldots + \phi_{31,p}LA_{t-p} \\
&+ \phi_{32,1}LO_{t-1} + \phi_{32,2}LO_{t-2} + \ldots + \phi_{32,q}LO_{t-q} \\
&+ \phi_{33,1}WS_{t-1} + \phi_{33,2}WS_{t-2} + \ldots + \phi_{33,r}WS_{t-r} \\
&+ C_3
\end{aligned}
\tag{34}
$$

but these models were ruled out after estimating their parameters by least squares using SAS. The models for all the latitude bands showed little explained error, with high Mean Squared

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Error (MSE) and very low R^2 statistics. This suggested that the series are indeed nonstationary, and probably should be differenced.

Accordingly, differenced models were chosen over the non-differenced models to improve explanatory capability. The differenced latitudes (LA_t-LA_{t-1}) or longitudes (LO_t-LO_{t-1}) will be referred to as latitude or longitude velocities henceforth.

3.1.3 *Separation into Latitude Bands* Based on Curry's analysis, it was believed that the model parameters should be allowed to change as the storm moved. This involved a threshold model as described in Section 2.3. Thus, the hurricane tracks were segmented by latitude bands five degrees in width, 10-15N, 15-20N, 20-25N, 25-30N, 30-35N, 35-40N and 40-45N in degrees latitude. When a hurricane crossed into another latitude band, the parameters for the new latitude band were used for the next forecast. Models were made for latitude and longitude in each of these bands separately which allowed the parameters to change as the storm moved. When the forecast latitude enters a new latitude band, the models associated with that new latitude band is used.

As discussed in Chapter 2, the data, to which the models for each latitude band were fit, included all position reports within that band plus the five position reports obtained before a storm moves into that band. Accordingly, the data base used in this research was arranged in rows wherein each row contained the present position report of a storm (its latitude, longitude and wind speed), and the five most recent values of the latitude velocities, longitude velocities and wind speeds. This allowed for many more observations in each latitude band than Curry's procedure allowed.

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3.2 Model Building

The parameters for each model were estimated using the SAS regression procedure (PROC REG) applied to the set of 351 storms occurring in the period from 1945-1983. This section describes the methods used to identify, specify and estimate the parameters of the multiple models for this research. The identification and specification of the variations of forecasting models will be discussed for position models and wind speed models.

3.2.1 *Position Models*

The position models forecast the latitude and longitude coordinates of the eye of a hurricane. Each model has a set of latitude and longitude equations for each of the seven latitude bands (see section 3.1.3). The latitude band models have the general form of an fifth-order autoregressive (AR(5)) model applied to the latitude and longitude velocities, as follows:

$$
\begin{aligned}
LA_t - LA_{t-1} = \; & \phi_{11,1}(LA_{t-1} - LA_{t-2}) + \ldots + \phi_{11,5}(LA_{t-5} - LA_{t-6}) \\
& + \phi_{12,1}(LO_{t-1} - LO_{t-2}) + \ldots + \phi_{12,5}(LO_{t-5} - LO_{t-6}) \\
& + \phi_{13,1} WS_{t-1} + \ldots + \phi_{13,5} WS_{t-5} \\
& + C_1
\end{aligned}
\tag{35}
$$

$$
\begin{aligned}
LO_t - LO_{t-1} = \; & \phi_{21,1}(LA_{t-1} - LA_{t-2}) + \ldots + \phi_{21,5}(LA_{t-5} - LA_{t-6}) \\
& + \phi_{22,1}(LO_{t-1} - LO_{t-2}) + \ldots + \phi_{22,5}(LO_{t-5} - LO_{t-6}) \\
& + \phi_{23,1} WS_{t-1} + \ldots + \phi_{23,5} WS_{t-5} \\
& + C_2
\end{aligned}
\tag{36}
$$

where LA_t represents the latitude at time t, LO_t represents the longitude at time t, WS_t represents the maximum sustained wind speed at time t and C_1, C_2 and C_3 are constants. The significant independent variables change according to the selection process used in each model. All the models use six previous position reports (differenced once to obtain five velocities), unless the

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coefficient for a particular lag is zero. Eleven position models were evaluated in this research. Their properties and estimation processes are described according to the following four sections:

1. Curry Models (2 Models)

2. Univariate Models (3 Models)

3. Bivariate Models (3 Models)

4. Trivariate Models (3 Models)

Curry Models. These two forecast models have the general form shown in Equations (14) and (15), which is the model that Curry specified in his dissertation in which latitude and longitude are functions of each other at lags one and four. The first model is referred to as the CURRY model; its parameters were estimated in his research using only his stationary class 5 storms (see Table B.1).

The second model has the same dependent variables (lags 1 and 4) as Curry's model, but the coefficients were reestimated using all the storms (1945-1983), not just the velocity-stationary storms. This model is referred to as the CURRY NEW model. The latitude and longitude velocity coefficients for this model are summarized in Table B.2.

Univariate Models. Univariate autoregressive models were formulated to see if the dependence between latitude and longitude is significant. The model for each latitude band will include latitude velocity at time t (LA_t-LA_{t-1}) predicted by past latitude velocities only, and longitude velocity at time t (LO_t-LO_{t-1}) predicted by past longitude velocities only. The coefficients for all other dependent variables are zero.

The univariate models thus have the form:

$$LA_t - LA_{t-1} = \phi_{1,1}(LA_{t-1} - LA_{t-2}) + \phi_{1,2}(LA_{t-2} - LA_{t-3})$$
$$+ ... + \phi_{1,5}(LA_{t-5} - LA_{t-6}) + e_{1t} \qquad (37)$$

$$LO_t - LO_{t-1} = \phi_{2,1}(LO_{t-1} - LO_{t-2}) + \phi_{2,2}(LO_{t-2} - LO_{t-3})$$
$$+ ... + \phi_{2,5}(LO_{t-5} - LO_{t-6}) + e_{2t} \qquad (38)$$

The estimation technique that is recommended by Curry to use ordinary least-square regression was utilized, with past values of latitude (longitude) velocity as predictors for the current latitude (longitude) velocity. Pindyck and Rubinfeld support this by stating, "if the number of terms in the distributed lag is very small, the equation can be estimated using ordinary least-squares regression." (15:232) They go on to say that using lagged variables as independent variables in ordinary least-squares is uncomplicated, but it might lead to imprecise parameter estimates because of the presence of multicollinearity and also because a lengthy lag structure could use up a large number of degrees of freedom (15:232).

Multicollinearity arises when the lagged variables are highly autocorrelated. In time series studies, this is almost certain to occur to some degree since observations from time periods close together are presumed to be correlated. According to Makridakis, both the loss of degrees of freedom and the problem of multicollinearity can be resolved by eliminating all but one of the highly correlated variables from the model (8:616). To account for the possible loss of degrees of freedom, Curry limited the number of lags of latitude and longitude velocity he used in his model. Since, Curry felt that the effects of a storm's motion more than 36 hours prior was negligible, he used no more than five velocity lags. Since we agree with this assessment, the lag-5 velocity will be the largest used in the models for this research. Note, for example, that

the lag-5 latitude velocity is $LA_{t-5}-LA_{t-6}$, where LA_{t-6} is the latitude observed six time periods in the past, or 36 hours, prior to time t.

In this research, to further guard against the effects of multicollinearity, the STEPWISE and BACKWARD options in SAS regression procedure were used during parameter estimation. These options were used hypothesizing that they would aid in determining the actual order of the model by eliminating any lagged variables which would not change the explanatory power of the model by a significant amount. The STEPWISE and BACKWARD parameter selection options in SAS determine the variables that contribute the most by their influence on the R^2 (see Equation 5); only the variables that significantly affect R^2 are left in the model. The BACKWARD option selects the optimal variables for the model by fitting the entire model and then "one by one deleting variables until all the variables remaining in the model produce F statistics significant at the 0.10 level. At each step, the variable showing the least contribution to the model is deleted." (18:818) The STEPWISE option selects the optimal set of variables by bringing in the variables one at a time, and at each step checks the F statistic for significance at the 0.15 level with the variables included, then removes any variables that are not significant (18:818).

Three univariate models were formulated: (1) UNI FULL - a full univariate model which has all the parameters for the five lag velocities included in the model (see Table B.3), (2) UNI STEP - a stepwise univariate model with only the parameters of the significant velocities chosen by the SAS STEPWISE option (see Table B.4), and (3) UNI BACK - a backward univariate model with only the parameters chosen by the SAS BACKWARD option (see Table B.5).

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Bivariate Models. Curry's basic models expressed the latitude velocity at time t (LA_t-LA_{t-1}) as a function of past latitude and longitude velocities; and the longitude velocity at time t (LO_t-LO_{t-1}) as a function of past longitude and latitude velocities as well:

$$LA_t = LA_{t-1}+\phi_{11,1}(LA_{t-1}-LA_{t-2})+...+\phi_{11,5}(LA_{t-5}-LA_{t-6})$$
$$+ \phi_{12,1}(LO_{t-1}-LO_{t-2})+...+\phi_{12,5}(LO_{t-5}-LO_{t-6}) \qquad (39)$$
$$+ C_1$$

$$LO_t = LO_{t-1}+\phi_{21,1}(LA_{t-1}-LA_{t-2})+...+\phi_{21,5}(LA_{t-5}-LA_{t-6})$$
$$+ \phi_{22,1}(LO_{t-1}-LO_{t-2})+...+\phi_{22,5}(LO_{t-5}-LO_{t-6}) \qquad (40)$$
$$+ C_2$$

where the C_1 and C_2 constants and the ϕs are estimated using least squares regression. Three new bivariate models were formulated: (1) BI FULL - a full bivariate model (see Tables B.6 and B.7), (2) BI STEP - a stepwise bivariate model (see Tables B.8 and B.9) and (3) BI BACK - a backward bivariate model (see Tables B.10 and B.11).

Trivariate Models. These models incorporate maximum wind speed of past hurricane position reports as another explanatory variable The models for this variation are:

$$LA_t-LA_{t-1} = \phi_{11,1}(LA_{t-1}-LA_{t-2})+...+\phi_{11,5}(LA_{t-5}-LA_{t-6})$$
$$+ \phi_{12,1}(LO_{t-1}-LO_{t-2})+...+\phi_{12,5}(LO_{t-5}-LO_{t-6}) \qquad (41)$$
$$+ \phi_{13,1}WS_{t-1}+...+\phi_{13,5}WS_{t-5}$$
$$+ C_1$$

$$LO_t-LO_{t-1} = \phi_{21,1}(LA_{t-1}-LA_{t-2})+...+\phi_{21,5}(LA_{t-5}-LA_{t-6})$$
$$+ \phi_{22,1}(LO_{t-1}-LO_{t-2})+...+\phi_{22,5}(LO_{t-5}-LO_{t-6}) \qquad (42)$$
$$+ \phi_{23,1}WS_{t-1}+...+\phi_{23,5}WS_{t-5}$$
$$+ C_2$$

where LA_t represents the latitude at time t, LO_t represents the longitude at time t, WS_t represents

the maximum sustained wind speed at time t and C_1 and C_2 are constants. A forecast model for the maximum sustained wind speed is described in the next section. A wind speed forecast is needed since the position forecasts are dependent on the wind speed in these models, thus the position forecasts will need a wind speed forecast in calculating future values. The parameters were estimated using least-squares regression, as in the univariate and bivariate cases, with the addition of the wind speed as an extra dependent variable. Three multivariate models were formulated: (1) TRI FULL - a full order trivariate model (see Tables B.12 and B.13), (2) TRI STEP a stepwise trivariate model (see Tables B.14 and B.15) and (3) TRI BACK - a backward trivariate model (see Tables B.16 and B.17). The eleven position models are summarized in Table 3.1.

3.2.2 *Wind Speed Models*

The two incentives for formulating a model to forecast maximum sustained wind speed (WS) are: (1) a WS forecast is necessary in the trivariate position forecast models which use WS as an explanatory variable of latitude and longitude, and (2) a WS forecast will be beneficial to the hurricane forecaster as a prediction for storm intensity.

The WS was forecasted as a function of past wind speeds, latitude velocities and longitude velocities. The general form of the WS model is:

$$
\begin{aligned}
WS_t = \; &\phi_{31,1}(LA_{t-1}-LA_{t-2})+...+\phi_{31,5}(LA_{t-5}-LA_{t-6}) \\
&+ \phi_{32,1}(LO_{t-1}-LO_{t-2})+...+\phi_{32,5}(LO_{t-5}-LO_{t-6}) \\
&+ \phi_{35,1}WS_{t-1}+...+\phi_{33,5}WS_{t-5} \\
&+ C_3
\end{aligned}
\tag{43}
$$

where LA_t represents the latitude at time t, LO_t represents the longitude at time t, WS_t represents the maximum sustained wind speed at time t and C_3 is a constant.

The parameters were estimated using least-squares regression, as in the trivariate position forecast models, with the WS at time t (WS$_t$) as the dependent variable. Three multivariate models were formulated: (1) WS FULL - a full order trivariate model (see Table B.18), (2) WS STEP a stepwise trivariate model and (3) WS BACK - a backward trivariate model. The WS STEP and WS BACK models for all the latitude bands were equivalent, so the wind speed forecast model WS BACK (see Table B:19) will refer to the model selected by either option. The wind speed and position models are summarized in Table 3.1.

Table 3.1. Summary of Forecast Models.

Position Model	Dependent Variable Summary	Parameter Estimation Procedure	Table # in Appendix
1. CURRY	Lags 1 & 4 (Bivariate)	None. (Already Estimated)	B.1
2. CURRY NEW	Lags 1 & 4 (Bivariate)	SAS PROC REG (no option)	B.2
3. UNI FULL	All lags 1 - 5 (Univariate)	SAS PROC REG (no option)	B.3
4. UNI STEP	Selected lags from 1 - 5 (Univariate)	SAS PROC REG (STEPWISE option)	B.4
5. UNI BACK	Selected lags from 1 - 5 (Univariate)	SAS PROC REG (BACKWARD option)	B.5
6. BI FULL	All lags 1 - 5 (Bivariate)	SAS PROC REG (no option)	B.6, 7
7. BI STEP	Selected lags from 1 - 5 (Bivariate)	SAS PROC REG (STEPWISE option)	B.8 , 9
8. BI BACK	Selected lags from 1 - 5 (Bivariate)	SAS PROC REG (BACKWARD option)	B.10, 11
9. TRI FULL	All lags 1 - 5 (Trivariate)	SAS PROC REG (no option)	B.12, 13
10. TRI STEP	Selected lags from 1 - 5 (Trivariate)	SAS PROC REG (STEPWISE option)	B.14, 15
11. TRI BACK	Selected lags from 1 - 5 (Trivariate)	SAS PROC REG (BACKWARD option)	B.16, 17
Wind Speed Model	Dependent Variable Summary	Parameter Estimation Procedure	Table # in Appendix
1. WS FULL	All lags 1 - 5 (Trivariate)	SAS PROC REG (no option)	B.18
2. WS BACK WS STEP	Selected lags from 1 - 5 (Trivariate)	SAS PROC REG (BACKWARD and STEPWISE options)	B.19

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3.3 Forecasting

Once all the position and wind speed models had been estimated, the next step was to compare their abilities in forecasting hurricanes. Two sets of storm data were used for the comparisons, (1) the entire set of 351 storms used in model-building and (2) the test set of 45 storms. The FORTRAN code used is shown in Appendix H. The four main steps required in forecasting the hurricane tracks in the two data sets are as follows:

- Data Manipulation

- Retrieving Model Coefficients

- Calculating Forecasts

- Calculating Forecast Errors

3.3.1 *Data Manipulation* The two sets of data are the same as in Section 3.2.1. The data were put into matrices similar to those used for the model building data, where all the lags were stored on the same row as the current position report, except no differencing was used. The forecasts were stored on the same row as the lags and present values.

3.3.2 *Retrieving the Model Coefficients* Due to the multiple models which are used to forecast the three data sets of hurricane tracks, the model coefficients for each separate model were read into the forecast routine as matrices. This allowed forecasts based on the different models to be made easily. This is included in the FORTRAN code shown in Appendix H.

Each model had a separate set of latitude velocity, longitude velocity and wind speed coefficients for each latitude band, so the forecasting equations could change as the storm moved. Curry's latitude bands were again used (10-15N, 15-20N, 20-25N, 25-30N, 30-35N, 35-40N and 40-45N in degrees latitude).

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A wind speed forecast was included with all the position forecasts, which does not affect the position forecasts except in the trivariate models. The wind speed forecast was necessary in developing position forecasts using the trivariate models which used the wind speeds as a dependent variable.

3.3.3 *Calculating Forecasts* The forecasts were made using the basic models shown in Equations 41, 42, and 43 for latitude, longitude and maximum sustained wind speed, respectively. The coefficients depend on the model being used to obtain the forecasts. If a particular coefficient is not significant or not used in the model (example: if STEPWISE did not select it for inclusion in the model), then the coefficient is set to zero. The method for forecasting hurricane position is the identical to Curry's method, and is stated as follows:

> The one step ahead forecast position (LA_t, LO_t) is based on the use of the (six) previous (six hour) position reports. To obtain the two step ahead forecast, (LA_t, LO_t) is treated as the last observed position, and the one step ahead forecast (from time t) is computed. Forecasts for lead times up to n steps ahead are computed in a similar manner. (4:65)

This method is assumed to be appropriate for this application and is duplicated in obtaining the maximum sustained wind speed forecasts. One drawback to this method is that any errors which occur in the first step (6 hour) forecast are likely to carry through all the forecasts, and any errors which occur in the second step forecast are likely to carry through subsequent forecasts. However, since the model parameters are allowed to change when a hurricane crosses into a new latitude band, this error would be hard to eradicate. Also, irregardless of whether the last observed position is a actual or forecasted position, the appropriate forecast equations are determined by the latitude band that the last observed position is in.

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3.3.4 *Calculating Forecast Errors* Once the forecasts had been calculated and stored, the forecast errors could be calculated. Forecast errors were computed for the 6-, 12-, 24-, 48-, and 72-hour forecasts, as recommended by Curry. The primary measure is the great circle distance (GCD), which is the distance between the actual (LA,LO) and the forecasted (LA$_t$,LO$_t$) position of the eye of the hurricane in nautical miles (see Equation (26)). The statistics used for the model comparisons were mean errors (MEAN), the standard deviations (STD) of the errors, and the mean squared prediction error (MSPR), as given by Equations (27,) (28), and (29), respectively. The forecast errors of the latitude coordinates, longitude coordinates and maximum sustained wind speeds were also calculated and evaluated using the same statistics.

3.4 Model Selection

The model which showed the most overall accuracy when used to forecast the two hurricane data sets was selected as the best forecasting model. The model coefficients of this selected model were then recalculated incorporating all the storms from the test set (45 storms) and the model-building set (351 storms), which will be referred to as the FINAL model. The error analysis for the FINAL model was based on forecast errors of the combined data set (396 storms) and its predictive abilities compared to the other models. The forecasting results are summarized in the next chapter.

IV. Forecasting Results

This chapter provides a discussion of the forecasting results in applying Curry's model and the ten new models to the historical hurricane tracks. The areas discussed are

- Model Analysis

- Forecast Results

- Final Model

4.1 Model Analysis

The eleven different models examined in this research are summarized in Table 3.1, and their fitted parameter estimates are presented in Appendix B. This section describes how the parameters of these models give some information about hurricane movement. It is broken down into two sections:

- Order of the Models and Persistence

- Dependence Between Variables

4.1.1 *Order of the Models and Persistence* The lag-four coefficients produced by the STEPWISE and BACKWARD options are seldom significant enough to be included in a model. This contradicts Curry's decision to use the lag-four parameter to capture the "diurnal effect of the sun (the slowing down of the storm at night)." (4:99) The lag-one parameter was included the most often, and the lag-two parameter was the second most often included. This means that the future storm movement is best captured by the most recent history of the storm, which Curry refers to as persistence. This is also true for wind speed, which is primarily predicted by its most recent past wind speeds alone.

In addition, when observing the significant coefficients in the latitude velocity models, the past latitude velocities appear to be the best predictors. This makes sense since the latitude velocity is expected to be driven more by its past latitude velocity than by its longitude velocity. The longitude velocity is best predicted with past longitude velocities and the wind speed is best predicted by past wind speeds. However, the coefficients show that, in the middle latitude bands (20-25 and 25-30), the latitude and the longitude velocities show a great deal of interdependence. This can be seen by examining the coefficients that are significant in the TRI BACK model (see Tables B.16 and B.17). This presumably corresponds to where the storms start to change direction from primarily toward the west and north to toward the east and north.

4.1.2 *Dependence Between Variables* Examining the coefficients in the various models, it seems that longitude is a better predictor for latitude as opposed to latitude as a predictor for longitude, but only in the lower and middle latitude bands (10-15, 15-20, 20-25, and 25-30). In the other latitude bands, neither latitude or longitude depends greatly on the other. This contradicts Curry's conclusion. He states that "latitude seems to be a better predictor of longitude as opposed to predicting via the reverse relationship." (4:99)

In predicting wind speed, neither latitude or longitude show much significance in the models (see Table B.19), but when latitude velocity coefficients are significant, they usually correspond to the lag-one or lag-two terms. On the other hand, when longitude velocity parameters are significant, they usually correspond to lag-four or lag-five terms.

4.2 Forecast Results

The procedures for forecasting (see Section 3.3) were used to develop the 6-, 12-, 24-, 48- and 72-hour forecasts on all eleven models. Wind speed forecasts were also examined, and for simplicity, only the WS BACK model will be used to forecast wind speed for the remainder of this research. The WS BACK model was chosen since (1) it was identical to the WS STEP model, (2) it performed about the same as the WS FULL model, and (3) there are fewer parameters in the WS BACK model than in the WS FULL model. Since WS BACK models wind speed as a function of previous wind speeds and previous latitude and longitude velocities, it must be used in conjunction with a position model in order to obtain forecasts for times greater than 6 hours ahead.

The great circle distance was the primary measure of accuracy, although the errors in latitude and longitude were also examined. The great circle distances (GCD) were calculated (see Equation 26) for every 6-, 12-, 24-, 48-, and 72-hour forecast for the storms in the model-building data set (351 storms) and the test data set (45 storms). The analysis on the GCD is done separately in each data set. The statistics used to analyze GCD were the mean (MEAN), the standard deviation (STD), and the mean squared prediction error (MSPR) (see Equations 27, 28, and 29). This section is broken down into two areas:

- Model-Building Data (Validation)

- Test Data

4.2.1 *Model Building Data (Validation)* Forecasts were made for each of the 351 storms in the model-building data set for validation purposes. The objective was twofold: (1) to identify any incongruities in the models which could not be attributed to expected normal errors and (2) to get a first look at the forecasting abilities of the models.

MEAN and STD. The MEAN and STD values for GCD (great circle distance), wind speed error, latitude error, and longitude error of the 6-, 12-, 24-, 48-, and 72-hour forecasts are summarized in Tables C.1-C.5. In each case, WS BACK is used to forecast wind speeds in conjunction with the specified position model. The TRI BACK model had the consistently lower MEAN and STD in all the forecast periods. The CURRY NEW model also performed quite well, which may indicate that Curry's determined order may be satisfactory.

MSPR. The MSPR values for GCD, wind speed error, latitude error, and longitude error of the 6-, 12-, 24-, 48-, and 72-hour forecasts are summarized in Tables C.6-C.10. The TRI BACK model had the lowest MSPR in the all the forecast periods, which would mean that forecasting on this set of hurricanes the TRI BACK model would be best. The CURRY model had the highest MSPR in all of the forecast periods, which would be as expected since its coefficients were estimated using only certain storms. The latitude and longitude MSPRs concurred that the best model was the TRI BACK model.

4.2.2 *Test Data* Forecasts were also made on the test data set (45 storms during the period 1984-1989) in order to find the model that had the best 24-, 48-, and 72-hour forecasts.

MEAN and STD. The MEAN and STD values for GCD, wind speed error, latitude error, and longitude error of the 6-, 12-, 24-, 48-, and 72-hour forecasts computed over the test set are summarized in Tables D.1-D.6 using the WS BACK model. Once again, the TRI BACK model

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had the consistently lower MEAN and STD in all the forecast periods, especially in the 48-hour forecasts. It is interesting to notice that in the 72-hour forecast the CURRY model has the lowest MEAN GCD, but it has the highest STD, which means it is the most variable forecast model. In the 72-hour forecasts, the TRI BACK model has the next lowest MEAN and it has the lowest STD

MSPR. The MSPR values for GCD, wind speed error, latitude error, and longitude error of the 6, 12, 24, 48, and 72-hour forecasts for the test set are summarized in Tables D.6-D.10 using the WS BACK model in conjunction with each position model to forecast wind speed. The TRI BACK model had the lowest MSPR for the 48 and 72-hour forecasts, the BI FULL model had the lowest MSPR for the 12 and 24-hour forecasts, and the CURRY NEW model had the lowest MSPR for the 6-hour forecasts. This would suggest that Curry's order and model selection might be appropriate, but the longer forecasts could be improved by using the TRI BACK model. The CURRY model still had the weakest performance of all the models for each of the forecasts.

The latitude and longitude MSPRs concurred with the best model being TRI BACK. In addition, these MSPRs show that the univariate models, UNI FULL and UNI BACK, predicted the latitude coordinates well. This suggests that the longitude is not a good predictor of latitude, since in the univariate models no dependence between latitude and longitude was accounted for. This confirms Curry's observations that longitude is a good predictor of latitude (4:99). The summary statistics from the test data set forecasts confirm that the TRI BACK model would be the best model (from this set of eleven models) to predict any hurricane.

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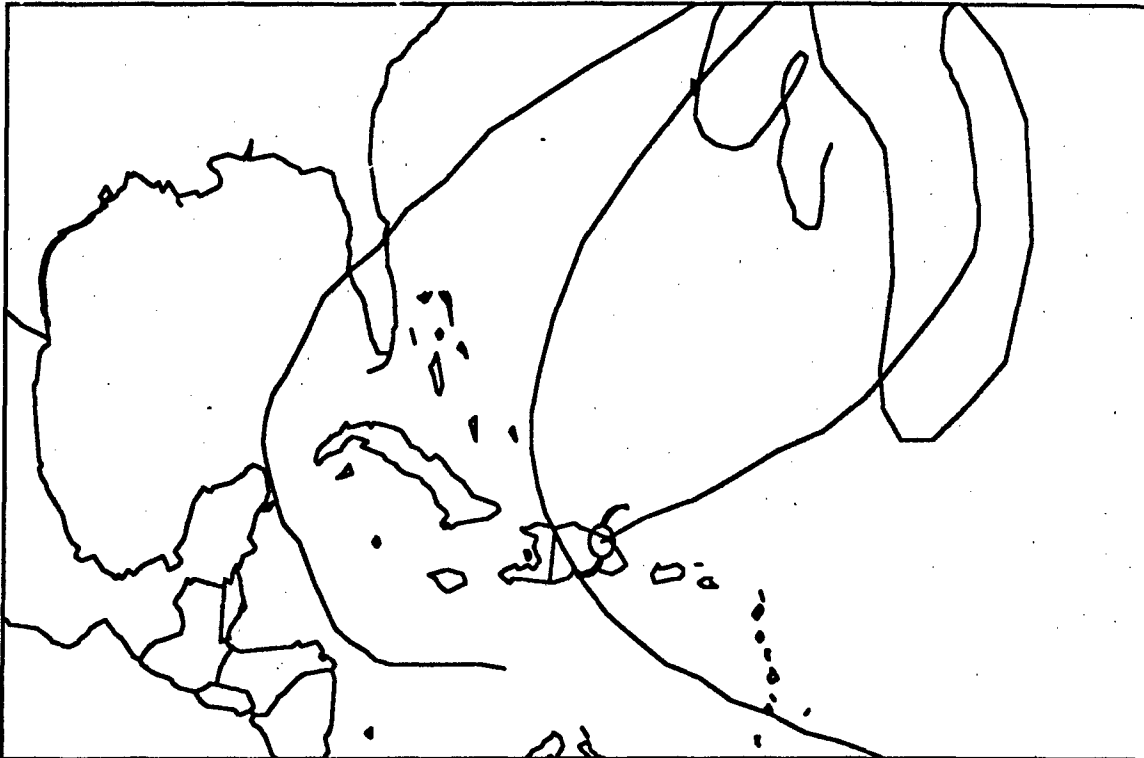
Figure 4.1. The Plot of Four Hurricanes Which Did Not Exhibit the Typical Hurricane Path

Histograms. The histograms for all the forecast periods for both the test set and model-building set are shown in Appendix F. The GCD errors appear to be Normal (GCD is an absolute error measurement, so a Normal distribution associated with it will be truncated), but the existence of a few very large GCDs would suggest that some of the storms did not behave like typical hurricanes. After examining the tracks of four of the storms that produced these outliers, it is apparent that these tracks do not exhibit the typical hurricane path (see Figure 4.1). Since the object of this research was to modify Curry's model to best forecast all the storms, these storms were left in both the model building and testing phases.

Latitude Band Summary. The forecast errors in the separate latitude bands show greater errors in forecasting occur as the storms move north (see Appendix E).

4.3 Final Model

The model comparison analysis suggested that the TRI BACK model was the best model since it displayed the best overall forecasting results of the eleven models. The next step was to recalculate the TRI BACK model parameters using the two sets of data combined, which included 396 storms with over 10500 observations. The new model will be referred to as the FINAL model. This section focuses on model identification and forecasting.

4.3.1 *Model Identification* The parameters for forecasting latitude, longitude and maximum sustained wind speed as functions of each other were estimated using SAS PROC REG with the BACKWARD option. The estimated models for each latitude band are listed in Appendix A, and the coefficients for latitude velocities, longitude velocities and maximum sustained wind speed are summarized in Tables B.20, B.21 and B.22.

There seems to be a strong interdependence between the three variables, since in many of the models there exists significant parameters for all three of the variables. In general, latitude velocity depends mostly on past latitude velocities; but many longitude velocities and a few past wind speeds are also included. Longitude velocities depend heavily on past longitude velocities. Wind speed is primarily a function of past wind speeds, as expected. The model R^2 values for all the models range from 0.647 to 0.972, with the larger values from wind speed models. Since the higher R^2 values are from the models for predicting wind speed, we would expect the wind speed to be predicted most accurately with these models. The lower R^2 values for latitude and longitude velocities appeared in the 20-25N degree band, and, more generally, the lower values were in the most southern bands (10-15N, 15-20N and 20-25N degrees).

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4.3.2 *Forecasting* The forecasts for the FINAL model were made with the same procedures in Sections 3.3 and 4.2, except that the test set was included in the model-building set. The primary forecast evaluation tools for this model are the model-building data set (396 storms) and an example hurricane track. Hurricane Hugo (1989) was chosen, since its the position reports were easily available and because it caused significant damage to a highly populated area.

Model-Building Set (396 storms). The entire set of data (396 storms) was forecasted using the FINAL model, the CURRY model, and the TRI BACK model. These three models were used to compare the forecasting abilities between the CURRY model and the FINAL model, and to also to compare the TRI BACK model with the FINAL model to see if using the entire data set to estimate the parameters effects the forecasting ability.

Summary Statistics. The primary measure GCD is used (see section 4.2.1) to compare these models using this set of hurricane tracks; the summary tables are in Appendix G. Both the WS BACK and the FINAL wind speed models were used separately to allow comparison between models without having to determine how much of the variance in the forecast errors is due to the wind speed model errors, since our main focus is to compare position forecast ability. The summary tables show that both wind speed models forecasted wind speed similarly with virtually no affect on the position forecasts.

The overall summary statistics for the GCD MSPR (Tables G.1 and G.3) show that the TRI BACK and FINAL models have equivalent position forecasting ability, and both are better than the CURRY model in all forecast periods. The GCD MEAN and STD results (Tables G.2 and G.4) also show that the TRI BACK and FINAL models have lower mean errors and lower

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standard deviations than the CURRY model. The 72-hour forecast will be tested using tests of hypotheses on the means and variances of two Normal distributions, to see if there is significant differences between the CURRY model and the FINAL model. The 72-hour forecast is used due to its importance in hurricane forecasting. Normality will be assumed since the number of observations is high (minimum of 377 observations).

Test of the Means. A hypothesis test of the two model means (17:289-290) GCD at the 72-hour forecast shows that there is a significant difference in the means at the 0.0005 level:

$$H_o: \quad \mu_{CURRY} = \mu_{FINAL}$$

$$H_1: \quad \mu_{CURRY} > \mu_{FINAL}$$

$$t_o^* = \frac{\bar{X}_{CURRY} - \bar{X}_{FINAL}}{\sqrt{S^2_{CURRY}/n_{CURRY} + S^2_{FINAL}/n_{FINAL}}}$$

$$= \frac{28.5}{5.93}$$

$$= 4.803$$

$$t_{CRIT} = t_{.0005,\infty} = 3.291$$

where we reject H_o, since $t_o^* > t_{critical}$. We can strongly conclude that the 72 hour GCD mean for the FINAL model is less than the CURRY model (17:288).

Test of the Variances. The hypothesis test on the 72-hour forecast GCD variances (17:295-296) of the two models also shows a significant difference:

$$H_o: \quad \sigma^2_{CURRY} = \sigma^2_{FINAL}$$

$$H_1: \quad \sigma^2_{CURRY} > \sigma^2_{FINAL}$$

$$F_o = \frac{S^2_{CURRY}}{S^2_{FINAL}}$$

$$= \frac{(283.6)^2}{(240.2)^2}$$

$$= 1.394$$

$$F_{CRIT} = F_{.01, \infty, \infty} = 1.00$$

where we reject H_o, since $F_o > F_{critical}$. We can strongly conclude that the 72-hour forecast error (GCD) variance for the FINAL model is less than the CURRY model (17:295). Based on this analysis, we can conclude that the hurricane forecast ability for the FINAL model is better than Curry's final model over the entire hurricane data set.

Hurricane Hugo. The FINAL, TRI BACK and CURRY models were used to forecast the 1989 hurricane Hugo. Hugo devastated the North Carolina coastline and caused damages that exceeded millions of dollars. Table 4.1 shows the overall forecasting statistics of the three models. The TRI BACK and FINAL models showed similar forecasting ability, which is expected since they are both similar models. The CURRY model did not perform as well. Figures 4.2 and 4.3 show the actual track of hurricane Hugo and the 72-hour forecast tracks that were made 72 hours before it actually hit the coastline using the CURRY model and the FINAL

Table 4.1. The Forecast Error Summary Statistics for Hurricane Hugo (1989).

FORECAST	#	MEAN(NM)	STD	WS MEAN	WS STD
CURRY					
6HR	42.	22.3969	38.2536	-0.5113	8.1422
12HR	42.	59.7075	86.5630	-1.2497	14.9071
24HR	41.	146.0242	204.0455	-2.3709	25.7854
48HR	41.	376.8226	400.4484	-4.0553	30.6029
72HR	40.	600.9904	519.5353	-1.9381	27.9269
FINAL					
6HR	42.	20.2171	31.0682	-0.4479	8.1365
12HR	41.	47.4721	51.0166	-0.8859	14.9887
24HR	40.	105.8161	119.8206	-1.7695	25.6510
48HR	39.	256.6896	203.2172	-3.8079	29.8377
72HR	36.	390.9282	267.6997	-5.6445	25.2889
TRI BACK					
6HR	42.	20.8542	32.6635	-0.5113	8.1422
12HR	41.	46.8584	51.0597	-0.9575	15.0223
24HR	40.	104.6282	121.4189	-1.9029	25.6006
48HR	39.	250.1266	199.5878	-3.9065	29.7214
72HR	36.	383.6379	273.4965	-5.2186	25.5723

model, respectively. The hurricane symbol marks the end of the 72-hour forecast track in each figure, while the track for hurricane Hugo continues through the Northeastern part of the United States. Neither model made a very accurate 72-hour forecast of Hugo, both expecting Hugo to still be well out at sea, although the CURRY model did have a smaller error (see Table 4.2).

Figures 4.4 and 4.5 show the actual track of hurricane Hugo and the 48-hour forecast tracks that were made 24 hours before it actually hit the coastline using the CURRY model and the Final model, respectively. The 48-hour forecasts were used to illustrate how the FINAL

Table 4.2. The Landfall GCD Forecast Errors for Hugo.

	72 HOURS FROM LANDFALL		24 HOURS FROM LANDFALL	
FORECAST PERIOD	FINAL FORECAST	CURRY FORECAST	FINAL FORECAST	CURRY FORECAST
6 HOUR	0.00	0.00	22.27	22.52
12 HOUR	55.67	19.14	70.35	101.30
24 HOUR	163.66	51.44	298.67	449.22
48 HOUR	422.16	230.05	LAND	LAND
72 HOUR	697.08	495.45	LAND	LAND

model had a forecast track right through the actual landfall position of Hugo (Charleston, SC) even though the actual extrapolated prediction for landfall would be closer to 48 hours rather than 24 hours. The Curry model also predicted landfall to occur in 48 hours but the location of landfall was far south of Charleston.

Hugo was a very fast moving storm with acceleration towards Charleston. The ability to account for any accelerations of its movement are exactly what Curry's model cannot model since it only used storms that were latitude and longitude stationary in velocity. The FINAL model does seem to forecast these accelerations better, and give a more accurate forecast.
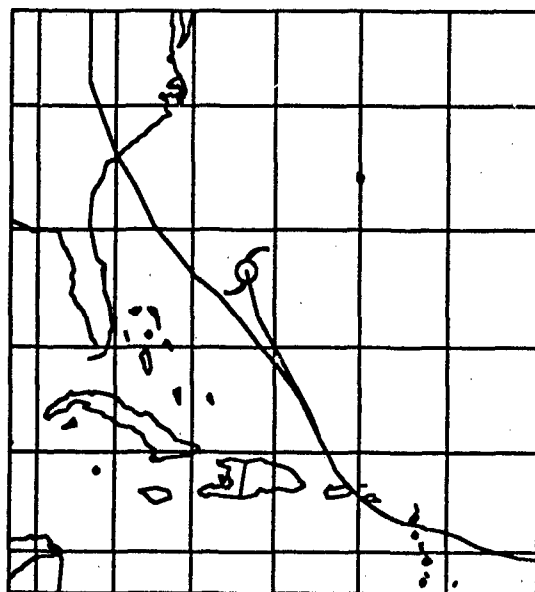
Figure 4.2. CURRY 72-hour Forecast Tracks of Hugo at 72 Hours from Landfall.
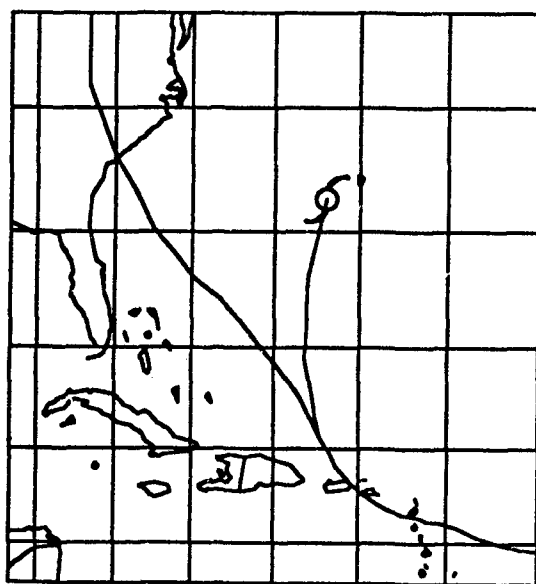
Figure 4.3. FINAL 72-hour Forecast Tracks of Hugo at 72 Hours From Landfall.

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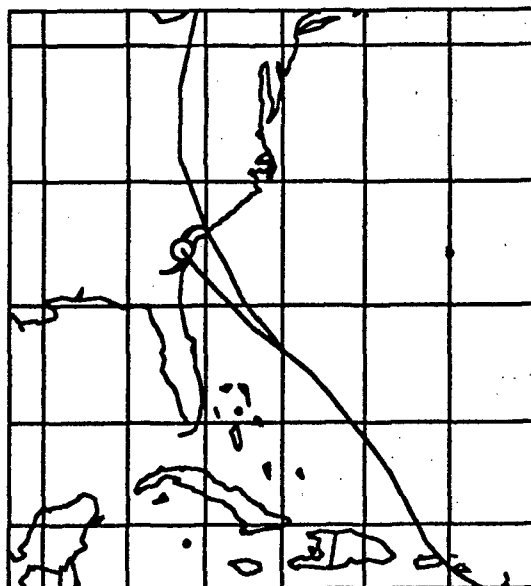
Figure 4.4. CURRY Landfall Prediction of Hugo 24 Hours Away from Actual Landfall.
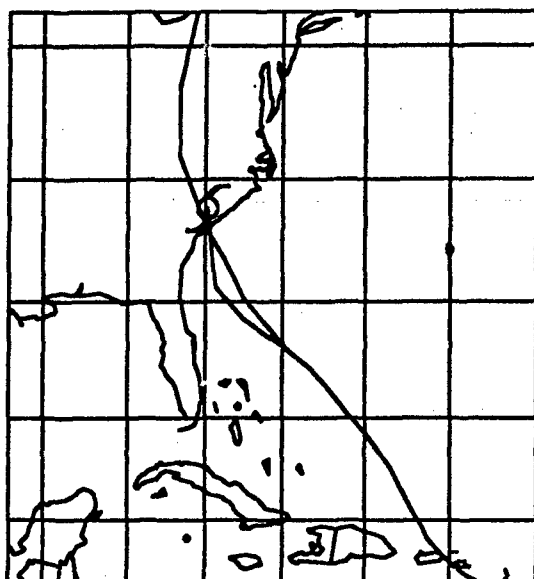
Figure 4.5. FINAL Landfall Prediction of Hugo 24 Hours Away from Actual Landfall.

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V. Conclusions and Recommendations

The results of Chapter IV are summarized in this chapter, as they relate to forecasting hurricane movement. Some recommended topics for future research are also discussed.

5.1 Hurricane Modeling Conclusions

The objectives of this research were: (1) to modify Curry's threshold autoregressive time series model to improve its ability to forecast all types of hurricanes, (2) to forecast the maximum wind speed sustained for a hurricane, and (3) to include past maximum wind speeds as an explanatory variable to aid in forecasting hurricanes.

The first problem encountered in this research was eliminating position reports following landfall (see section 3.1.1), since the forecast over land is not crucial. Creating a boundary for landfall solved this problem and gave the flexibility to include hurricane tracks that moved through the Florida peninsula towards the Gulf Coast communities.

The next concern involved the stationarity classifications that Curry used (see Section 3.1.2). It was concluded that the stationarity classifications would create complications when forecasting a storm in real-time. There is no way of telling what stationarity class the storm is in until many position reports are collected, and a storm may change classes several times in its duration. Accordingly, the stationarity classification was dropped from the model to estimate new parameters using all the storms.

One of the major contributions of this research was the construction of the data files (see Section 3.1.3), which allowed for many more observations to be included in estimating the parameters. This allowed for stronger conclusions to be made about forecasting results and

parameter estimation. One of Curry's issues involved the limited number of useful observations he had to work with. It is felt that if Curry used this new strategy for constructing the data files, he might meet all of his original objectives.

The eleven models used in this research involved slight modifications to Curry's model. After estimating the parameters, each model was used to forecast the hurricanes in a test set so the forecast abilities of the different models could be compared. The model that most accurately forecasted the 396 storms in the data base was a trivariate threshold autoregressive time series model (see Appendix A) referred to as the FINAL model. This forecast model predicts latitude velocity, longitude velocity and wind speed as functions of each other for forecasts up to 72 hours. It was estimated using SAS REG with the BACKWARD option. By determining the order using BACKWARD, some of the information that Curry lost by leaving out all lag 2, lag 3, and lag 5 explanatory variables was gained, but with less risk of overspecifying.

The FINAL model had average 24-, 48-, and 72-hour forecast errors of 103, 243, and 376 nautical miles, while Curry's model had forecast errors of 120, 269, and 405 nautical miles. Accordingly, it is conjectured that the FINAL model would improve on Curry's average errors.

In addition, a model to forecast the maximum sustained wind speed had to be estimated to use the wind speeds properly in the latitude and longitude forecast models. These maximum sustained wind speed forecasts should be helpful to the hurricane forecaster. The wind speed model used in this research gave mean errors and standard deviations of -0.1 and 15.4 miles per hour (MPH) for the 24-hour forecast, 1.6 and 21.6 MPH for the 48-hour forecast, 3.4 and 24.5 MPH for the 72-hour forecasts. In other words, the model forecasts maximum sustained wind speed with a mean error of within 4 MPH.

5.2 Future Hurricane Modeling

This model demonstrates that improvements can be gained in predicting the movement of hurricanes. This section describes some future research which might improve our forecasting ability even more. The areas that future research might focus on include:

- Using the Autocorrelation Model

- Increase Number of Latitude Bands

- Modeling the Hurricane Outliers Separately

5.2.1 *The Autocorrelation Model* One of the problems encountered when formulating the model for the hurricane data was the need to combine the cross-section (independent storms) and time series data (individual position observations), see Section 2.4. Pooling data was necessary since we wanted to examine the history of hurricane motion to find general patterns, trends or persistence that hurricanes may share. Pindyck and Rubinfeld's autocorrelation model, described in Section 2.4, may be a good means to accomplish pooling of the hurricane data without losing any observations due to the independent storms.

5.2.2 *Increasing the Number of Latitude Bands* The threshold model used in this research duplicated Curry's model (see Section 2.3), which was developed to allow the model coefficients to change as the storm travelled through the Atlantic. One of the reasons that Curry segmented the Atlantic into only seven latitude bands was his lack of sufficient data in each of the bands once the lagged data was made "storm unique" (1:106). In this research, a different technique for breaking the data into latitude bands (see Section 3.1.3) allowed many more observations to be used for developing models in each latitude band. Accordingly, it may be beneficial to segment the Atlantic into more regions, since the data is available. This would

allow the model to better reflect any effects the location of a hurricane has on its motion. The belief that the region of the ocean the storm is in has an impact on its motion is one of the hypothesis that drove Curry's research effort (4:105).

5.2.3 *Modeling the Hurricane Outliers Separately*   One of the factors creating some of the large forecast errors was the existence of certain storms which did not exhibit typical hurricane tracks (see Figure 4.1). These tracks could not be accurately forecasted since they did not exhibit any of the underlying patterns, trends and persistence that are common in the majority of the past hurricane tracks. In addition, the inclusion of these storms in the parameter estimation phase might possibly weaken the ability of the model to accurately model the majority of hurricane tracks which do possess common tracks. By estimating the model parameters without these storms, the model's forecasts of normal hurricane tracks could be more accurate, at the expense of its ability to forecast the unusual tracks.

One solution to this problem might be to model the normal hurricane tracks separately from the abnormal tracks. Unfortunately, the forecaster would have a hard time telling which model to use in the early stages of the hurricane, if ever. The key would be to find some underlying correlations or factors in these abnormal tracks which would allow the forecaster to determine when their occurrence is most likely. Once this is determined, the forecaster could decide which model to give more consideration.

In this research, the four storms from the test data, which gave 72-hour forecast errors above 1000 nautical miles when forecasted using the TRI BACK model, were inspected (see Figure 4.1). This examination revealed that all these abnormal storms materialized after September 15th (late season storms). This may suggest that the late season storms should be

modeled separately from all other storms, which may give a better forecast for the early season storms, thus reducing the overall forecast errors.

5.3 Overall Evaluation

The FINAL model, see Appendix A, shows more promise than Curry's model for forecasting hurricanes because it shows a significant improvement in mean and variance in forecast errors. An added feature of the FINAL model is that it would predict the maximum sustained wind speed of the 72-hour forecast with mean error of less than 4 miles per hour. This makes the FINAL model even more valuable to the hurricane forecaster, since one of the emerging issues in the 19th Conference on Hurricanes and Tropical Meteorology (May 1991), was the ability to predict the intensity of a storm.

Before presenting this model to the NHC, the recommendations should be implemented. These enhancements should significantly improve the models ability to forecast hurricane movement. In the mean time, this model could be programmed for a personal computer to use as a supplementary tool for the hurricane forecaster.

Appendix A. The FINAL Model

These are the recommended latitude band models for forecasting the positions and maximum wind speeds of tropical storms and hurricanes. The models were estimated using the past velocities of latitude and longitude, and the past wind speeds of 396 storms from 1945-1989. Hurricane official reports are made at 6 hour intervals, at 000Z, 0600Z, 1200Z and 1800Z.

In the models, the subscripts refer to the time period of the variable, where a hurricanes present report is referred to as t-1, and the previous report is referred as t-2, two reports previous is t-3, and so on. These models can be used to find the one-step ahead (t) position and wind speed forecasts, then the two-step ahead (t+1) forecast can made using the (t) forecast as the (t-1) report, the present report (t-1) as the (t-2) report, and so on.

```
Latitude Band: 10-15 degrees N
```

$$LA_t = LA_{t-1} + 0.766(LA_{t-1} - LA_{t-2}) + 0.107(LA_{t-2} - LA_{t-3})$$
$$+ 0.088(LAt-4 - LA_{t-5}) - 0.143(LA_{t-5} - LA_{t-6})$$
$$- 0.105(LO_{t-1} - LO_{t-2}) + 0.054(LO_{t-2} - LO_{t-3}) + 0.038(LO_{t-5} - LO_{t-6})$$
$$+ 0.002(WS_{t-1}) - 0.002(WS_{t-5})$$
$$+ 0.065$$

$$LO_t = LO_{t-1} + 0.136(LA_{t-1} - LA_{t-2}) - 0.179(LA_{t-4} - LA_{t-5}) + 0.109(LA_{t-5} - LA_{t-6})$$
$$+ .840(LO_{t-1} - LO_{t-2}) + 0.116(LO_{t-3} - LO_{t-4})$$
$$- 0.001(WS_{t-1})$$
$$+ 0.085$$

$$WS_t = 1.457(LA_{t-1} - LA_{t-2})$$
$$+ 0.622(LO_{t-4} - LO_{t-5})$$
$$+ 1.516(WS_{t-1}) - 0.530(WS_{t-5})$$
$$+ 0.586$$

Latitude Band: 15-20 degrees N

$$LA_t = LA_{t-1} + 0.954(LA_{t-1} - LA_{t-2}) - 0.063(LA_{t-2} - LA_{t-3})$$
$$-0.034(LO_{t-2} - LO_{t-3}) + 0.038(LO_{t-5} - LO_{t-6})$$
$$+0.001(WS_{t-1}) - 0.001(WS_{t-3})$$
$$+0.044$$

$$LO_t = LO_{t-1} + .855(LO_{t-1} - LO_{t-2}) + 0.075(LO_{t-5} - LO_{t-6})$$
$$-0.005(WS_{t-2}) + 0.005(WS_{t-3})$$
$$+0.049$$

$$WS_t = 1.449(WS_{t-1}) - 0.425(WS_{t-2}) - 0.056(WS_{t-4})$$
$$+2.116$$

Latitude Band: 20-25 degrees N

$$LA_t = LA_{t-1} + 0.880(LA_{t-1} - LA_{t-2}) + 0.075(LA_{t-4} - LA_{t-5}) - 0.088(LA_{t-5} - LA_{t-6})$$
$$-0.206(LO_{t-1} - LO_{t-2}) + 0.078(LO_{t-2} - LO_{t-3})$$
$$+0.065(LO_{t-3} - LO_{t-4}) + 0.038(LO_{t-5} - LO_{t-6})$$
$$+0.091$$

$$LO_t = LO_{t-1} - 0.383(LA_{t-1} - LA_{t-2}) + 0.251(LA_{t-2} - LA_{t-3})$$
$$+0.634(LO_{t-1} - LO_{t-2}) + 0.093(LO_{t-3} - LO_{t-4})$$
$$+0.119(LO_{t-3} - LO_{t-4}) + 0.065(LO_{t-4} - LO_{t-5})$$
$$+0.058$$

$$WS_t = 1.529(LA_{t-1} - LA_{t-2})$$
$$+1.432(WS_{t-1}) - 0.464(WS_{t-2})$$
$$+1.817$$

Latitude Band: 25-30 degrees N

$$LA_t = LA_{t-1} + 1.036(LA_{t-1} - LA_{t-2}) - 0.157(LA_{t-2} - LA_{t-3})$$
$$+ 0.068(LA_{t-4} - LA_{t-5}) - 0.079(LA_{t-5} - LA_{t-6})$$
$$- 0.114(LO_{t-1} - LO_{t-2}) + 0.098(LO_{t-3} - LO_{t-4})$$
$$+ 0.002(WS_{t-3}) - 0.002(WS_{t-3})$$
$$+ 0.066$$

$$LO_t = LO_{t-1} - 0.382(LA_{t-1} - LA_{t-2}) + 0.251(LA_{t-2} - LA_{t-3})$$
$$+ 0.634(LO_{t-1} - LO_{t-2}) + 0.093(LO_{t-2} - LO_{t-3})$$
$$- 0.118(LO_{t-3} - LO_{t-4}) + 0.065(LO_{t-4} - LO_{t-5})$$
$$+ 0.058$$

$$WS_t = 0.389(LO_{t-5} - LO_{t-6})$$
$$+ 1.408(WS_{t-1}) - 0.399(WS_{t-2}) - 0.100(WS_{t-4}) + 0.045(WS_{t-5})$$
$$+ 2.116$$

Latitude Band: 30-35 degrees N

$$LA_t = LA_{t-1} + 1.081(LA_{t-1} - LA_{t-2}) - 0.253(LA_{t-2} - LA_{t-3})$$
$$+ 0.138(LA_{t-3} - LA_{t-4}) - 0.073(LA_{t-4} - LA_{t-5})$$
$$- 0.053(LO_{t-1} - LO_{t-2}) + 0.051(LO_{t-3} - LO_{t-4})$$
$$+ 0.001(WS_{t-1})$$
$$+ 0.019$$

$$LO_t = LO_{t-1} - 0.049(LA_{t-1} - LA_{t-2}) - 0.056(LA_{t-5} - LA_{t-6})$$
$$+ 1.102(LO_{t-1} - LO_{t-2}) - 0.073(LO_{t-2} - LO_{t-3})$$
$$- 0.081(LO_{t-3} - LO_{t-4}) - 0.043(LO_{t-5} - LO_{t-6})$$
$$- 0.039$$

$$WS_t = 0.422(LO_{t-5} - LO_{t-6})$$
$$+ 1.334(WS_{t-1}) - 0.224(WS_{t-2}) - 0.156(WS_{t-4})$$
$$+ 2.825$$

Latitude Band: 35-40 degrees N

$$LA_t = LA_{t-1} + 1.132(LA_{t-1} - LA_{t-2}) - 0.193(LA_{t-2} - LA_{t-3})$$
$$-0.057(LO_{t-1} - LO_{t-2}) + 0.129(LO_{t-4} - LO_{t-5})$$
$$-0.066LO_{t-5} - LO_{t-6})$$
$$+0.079$$

$$LO_t = LO_{t-1} - 0.129(LA_{t-3} - LA_{t-4})$$
$$+1.216(LO_{t-1} - LO_{t-2}) - 0.246(LO_{t-2} - LO_{t-3})$$
$$-0.078(LO_{t-5} - LO_{t-6})$$
$$+0.005(WS_{t-2}) - 0.005(WS_{t-4})$$
$$-0.103$$

$$WS_t = 1.359(WS_{t-1}) - 0.264(WS_{t-2}) - 0.142(WS_{t-3})$$
$$+2.380$$

Latitude Band: 40-45 degrees N

$$LA_t = LA_{t-1} + 0.996(LA_{t-1} - LA_{t-2}) - 0.137(LA_{t-5} - LA_{t-6})$$
$$-0.070(LO_{t-3} - LO_{t-4}) + 0.064(LO_{t-4} - LO_{t-5})$$
$$+0.007(WS_{t-2}) - 0.005(WS_{t-4})$$
$$+0.029$$

$$LO_t = LO_{t-1} - 0.182(LA_{t-1} - LA_{t-2}) - 0.208(LA_{t-2} - LA_{t-3})$$
$$+1.062(LO_{t-1} - LO_{t-2}) - 0.152(LO_{t-2} - LO_{t-3})$$
$$+0.106(LO_{t-3} - LO_{t-4}) - 0.218(LO_{t-5} - LO_{t-6})$$
$$+-0.006(WS_{t-1} + 0.015(WS_{t-4}) - 0.013(WS_{t-5})$$
$$-0.153$$

$$WS_t = 1.163(WS_{t-1}) - 0.103(WS_{t-2}) - 0.167(WS_{t-3})$$
$$+4.300$$

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Appendix B. The Forecasting Models Coefficients

This Appendix summarizes the coefficients for the various models used in this study. The headings and variables used are as follows {the subscripts refer to the tth observation of a time series; for example, a hurricanes present report is referred to as $t-1$, and the previous report is referred as $t-2$, two reports previous is $t-3$, and so on}:

Position Variables

       LATD - The latitude velocity forecast $LA_t - LA_{t+1}$

       LOND - The longitude velocity forecast $LO_t - LO_{t+1}$

       LATD LAG 1 (to 5) - The lag 1 (to 5) latitude velocity $LA_{t+1} - LA_{t+2}$ ($LA_{t+5} - LA_{t+6}$)

       LOND LAG 1 (to 5) - The lag 1 (to 5) latitude velocity $LO_{t+1} - LO_{t+2}$ ($LO_{t+5} - LO_{t+6}$)

Wind Speed Variables

       WS - The maximum sustained wind speed forecast WS_t

       WS LAG 1 (to 5) - The lag 1 (to 5) maximum sustained wind speed WS_{t+1} (WS_{t+5})

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Table B.1. Curry's Bivariate Model.

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.048	.053	.054	.071	.072	.087	-.086
	LATD LAG 1	.696	.766	.849	.777	.746	.735	.7423
	LATD LAG 4	.101	-.106	.013	.016	-.015	-.094	.013
	LOND LAG 1		-.010	-.064	-.101	-.049	-.075	-.067
	LOND LAG 4		.014	.073	.083	-.011	.023	-.003
LOND	INTER-CEPT	.127	.139	.067	.052	-.044	-.109	-.205
	LATD LAG 1	.233	.012	.026	.103	.050	.0300	-.145
	LATD LAG 4	-.075	-.050	-.052	-.198	-.030	-.005	.125
	LOND LAG 1	.607	.775	.779	.837	.841	.881	.831
	LOND LAG 4	.251	.088	.121	.032	.068	.006	-.042

Table B.2. Bivariate Coefficients Using Curry's Determined Order.

		LATITUDE BANDS						
DEP VAR	INDEP VAR	10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.075	.039	.095	.076	.062	.075	.147
	LATD LAG 1	.844	.918	.874	.923	.949	1.017	1.033
	LATD LAG 4	-.003	-.020	.003	-.045	-.025	-.088	-.130
	LOND LAG 1	-.063	-.035	-.144	-.091	-.019	-.046	-.002
	LOND LAG 4	.045	.042	.093	.082	.022	.043	.008
STAT	R-SQR	.681	.7340	.663	.7959	.814	.800	.760
	MSE	.026	.033	.080	.064	.091	.121	.250
	# OBS	578	996	1344	1529	1256	1014	580
LOND	INTER-CEPT	.049	.062	.104	-.012	-.044	-.106	-.314
	LATD LAG 1	.119	-.042	-.247	.030	-.062	-.070	.0633
	LATD LAG 4	-.089	.032	.072	-.100	-.046	-.074	-.122
	LOND LAG 1	.874	.872	.689	1.014	1.004	1.048	1.028
	LOND LAG 4	.070	.056	.173	-.087	-.102	-.138	-.191
STAT	R-SQR	.834	.809	.597	.835	.861	.847	.782
	MSE	.046	.075	.230	.114	.135	.209	.518
	# OBS	578	996	1344	1529	1256	1014	580

Table B.3. LATD & LOND Univariate Coefficients (All Included).

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.053	.046	.074	.085	.065	.076	.171
	LATD LAG 1	.778	.976	.704	1.072	1.079	1.163	1.052
	LATD LAG 2	.105	-.097	.129	-.201	-.238	-.191	-.005
	LATD LAG 3	-.011	.018	.076	-.004	.118	.012	-.099
	LATD LAG 4	.113	-.023	.037	.101	.030	-.055	.089
	LATD LAG 5	-.171	.035	-.067	-.088	-.068	.022	-.171
STAT	R-SQR	.685	.733	.647	.795	.819	.801	.764
	MSE	.026	.033	.084	.064	.088	.120	.246
	# OBS	578	996	1344	1529	1256	1014	580
LOND	INTER-CEPT	.056	.051	.003	-.034	-.092	-.177	-.392
	LOND LAG 1	.867	.887	.488	1.068	1.113	1.269	1.057
	LOND LAG 2	-.036	-.081	.201	-.013	-.100	-.312	-.162
	LOND LAG 3	.118	.107	.121	-.149	-.065	.020	.160
	LOND LAG 4	.029	-.057	.052	.092	.069	.071	-.040
	LOND LAG 5	-.031	.076	.0231	-.082	-.124	-.137	-.213
STAT	R-SQR	.833	.811	.608	.835	.861	.851	.787
	MSE	.046	.074	.224	.114	.135	.204	.506
	# OBS	578	996	1344	1529	1256	1014	580

Table B.4. LATD & LOND Univariate Coefficients from Stepwise Procedure.

		LATITUDE BANDS						
DEP VAR	INDEP VAR	10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.053	.049	.075	.082	.065	.073	.169
	LATD LAG 1	.778	.975	.705	1.068	1.080	1.168	1.024
	LATD LAG 2	.010	-.080	.130	-.182	-.241	-.211	
	LATD LAG 3			.092		.135		
	LATD LAG 4	.107						
	LATD LAG 5	-.171		-.051		-.053		-.154
STAT	R-SQR	.685	.733	.647	.793	.819	.801	.762
	MSE	.026	.033	.084	.065	.088	.120	.246
	# OBS	578	996	1344	1529	1256	1014	580
LOND	INTER-CEPT	.053	.052	.007	-.034	-.092	-.177	-.396
	LOND LAG 1	.847	.864	.489	1.062	1.113	1.267	1.004
	LOND LAG 2			.204		-.122	-.300	
	LOND LAG 3	.102		.125	-.156			
	LOND LAG 4			.064	.092		.083	
	LOND LAG 5	-171		-.051	-.087	-.053		-.154
STAT	R-SQR	.833	.810	.607	.835	.861	.851	.785
	MSE	.046	.074	.224	.114	.135	.203	.509
	# OBS	578	996	1344	1529	1256	1014	580

Table B.5. LATD & LOND Univariate Coefficients from BACKWARD Procedure.

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.053	.049	.075	.085	.065	.073	.169
	LATD LAG 1	.778	.975	.705	1.072	1.080	1.168	1.024
	LATD LAG 2	.010	-.080	.130	-.204	-.241	-.211	
	LATD LAG 3			.092		.135		
	LATD LAG 4	.107			.098			
	LATD LAG 5	-.171		-.051	-.087	-.053		-.154
STAT	R-SQR	.685	.733	.647	.795	.819	.801	.762
	MSE	.026	.033	.084	.064	.088	.120	.246
	# OBS	578	996	1344	1529	1256	1014	580
LOND	INTER-CEPT	.053	.050	.007	-.034	-.092	-.177	-.393
	LOND LAG 1	.847	.882	.489	1.062	1.113	1.267	1.055
	LOND LAG 2		-.073	.204		-.122	-.300	-.157
	LOND LAG 3	.102	.074	.125	-.156			.138
	LOND LAG 4			.064	.092		.083	
	LOND LAG 5		.050		-.082	-.098	-.138	-.235
STAT	R-SQR	.833	.811	.607	.835	.861	.851	.787
	MSE	.046	.074	.224	.114	.135	.203	.505
	# OBS	578	996	1344	1529	1256	1014	580

Table B.6. LATD Bivariate Coefficients (All Included).

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.068	.035	.078	.084	.068	.072	.180
	LATD LAG 1	.782	.971	.897	1.048	1.066	1.137	1.046
	LATD LAG 2	.105	-.088	-.063	-.176	-.231	-.176	.013
	LATD LAG 3	-.011	.017	.065	.004	.115	.012	-.125
	LATD LAG 4	.123	-.030	.062	.081	.028	-.052	.103
	LATD LAG 5	-.178	.036	-.078	-.087	-.070	.013	-.175
	LOND LAG 1	-.110	-.016	-.215	-.131	-.057	-.062	-.030
	LOND LAG 2	.058	-.048	.105	.038	.043	.026	.089
	LOND LAG 3	-.004	.043	.039	.0530	.022	.000	-.113
	LOND LAG 4	.009	.006	.008	.086	-.022	.062	.051
	LOND LAG 5	.033	.025	.030	-.064	.018	-.030	.010
STAT	R-SQR	.693	.737	.676	.084	.068	.072	.180
	MSE	.026	.032	.078	.061	.088	.119	.246
	# OBS	578	996	1344	1529	1256	1014	580

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Table B.7. LOND Bivariate Coefficients (All Included).

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.048	.058	.053	-.010	-.044	-.113	-.356
	LATD LAG 1	.152	.023	-.403	.029	.004	-.006	.200
	LATD LAG 2	-.056	-.076	.231	-.011	-.094	-.051	-.283
	LATD LAG 3	.038	-.052	.041	.033	.002	-.050	.176
	LATD LAG 4	-.166	.130	-.000	-.152	.013	-.011	-.117
	LATD LAG 5	.071	-.044	.011	.040	-.026	-.003	-.020
	LOND LAG 1	.861	.890	.618	1.059	1.091	1.236	1.091
	LOND LAG 2	-.032	-.081	.092	-.005	-.108	-.294	-.206
	LOND LAG 3	.124	.109	.102	-.015	-.064	.006	.166
	LOND LAG 4	.032	-.062	.061	-.097	.070	.063	-.024
	LOND LAG 5	-.040	.076	.031	-.087	-.093	-.106	-.227
STAT	R-SQR	.837	.812	.625	.838	.864	.855	.792
	MSE	.214	.074	.215	.112	.133	.200	.498
	# OBS	578	996	1344	1529	1256	1014	580

Table B.8. LATD Bivariate Coefficients from Stepwise Procedure.

DEP VAR	INDEP VAR	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.068	.037	.078	.082	.065	.073	.169
	LATD LAG 1	.783	.971	.888	1.046	1.080	1.168	1.024
	LATD LAG 2	.099	-.075		-.179	-.241	-.211	
	LATD LAG 3					.135		
	LATD LAG 4	.116			.097			
	LATD LAG 5	-.177			-.097	-.053		-.154
	LOND LAG 1	-.109		-.208	-.113			
	LOND LAG 2	.058	-.063	.077				
	LOND LAG 3		.046	.061	-.100			
	LOND LAG 4			.036				
	LOND LAG 5	.037	.027					
STAT	R-SQR	.693	.736	.674	.803	.819	.801	.762
	MSE	.025	.033	.078	.062	.088	.120	.246
	# OBS	578	996	1344	1529	1256	1014	580

Table B.9. LOND Bivariate Coefficients from Stepwise Procedure.

DEP VAR	INDEP VAR	LATITUDE BANDS
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.043	.052	.061	-.008	-.048	-.118	-.373
	LATD LAG 1	.125		-.406	.030			.206
	LATD LAG 2			.274		-.094	-.108	-.230
	LATD LAG 3							
	LATD LAG 4	-.096			-.096			
	LATD LAG 5							
	LOND LAG 1	.839	.864	.623	1.056	1.092	1.241	1.089
	LOND LAG 2			.077		-.129	-.296	-.193
	LOND LAG 3	.110		.124	-.146			.138
	LOND LAG 4			.075	.090		.072	
	LOND LAG 5		.067		-.082	-.067	-.109	-.233
STAT	R-SQR	.836	.810	.624	.838	.864	.855	.791
	MSE	.046	.074	.215	.112	.132	.199	.498
	# OBS	578	996	1344	1529	1256	1014	580

Table B.10. LATD Bivariate Coefficients from BACKWARD Procedure.

		LATITUDE BANDS						
DEP VAR	INDEP VAR	10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.068	.042	.079	.084	.067	.071	.169
	LATD LAG 1	.783	.975	.876	1.045	1.068	1.149	1.024
	LATD LAG 2	.099	-.079		-.171	-.232	-.208	
	LATD LAG 3					.131		
	LATD LAG 4	.116		.087	.084			
	LATD LAG 5	-.177		-.081	-.088	-.055		-.154
	LOND LAG 1	-.109		-.205	-.113	-.059	-.041	
	LOND LAG 2	.058	-.058	.078		.061		
	LOND LAG 3		.065	.064	-.074			
	LOND LAG 4				.085		.043	
	LOND LAG 5	.037		.030	-.064			
STAT	R-SQR	.693	.735	.676	.804	.820	.803	.762
	MSE	.025	.033	.077	.061	.088	.119	.246
	# OBS	578	996	1344	1529	1256	1014	580

Table B.11. LOND Bivariate Coefficients from BACKWARD Procedure.

		LATITUDE BANDS						
DEP VAR	INDEP VAR	10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.043	.050	.061	-.002	-.048	-.119	-.373
	LATD LAG 1	.125		-.406				.206
	LATD LAG 2			.274		-.094		-.230
	LATD LAG 3						-.115	
	LATD LAG 4	-.096			-.077			
	LATD LAG 5							
	LOND LAG 1	.839	.882	.623	1.054	1.092	1.231	1.089
	LOND LAG 2		-.073	.077		-.129	-.262	-.193
	LOND LAG 3	.110	.074	.124	-.150			.138
	LOND LAG 4			.075	.091			
	LOND LAG 5		.051		-.076	-.067	-.063	-.233
STAT	R-SQR	.836	.811	.624	.838	.864	.854	.791
	MSE	.046	.074	.215	.112	.132	.199	.498
	# OBS	578	996	1344	1529	1256	1014	580

Table B.12. LATD Trivariate Coefficients (All Included).

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.070	.035	.076	.060	.019	.048	.010
	LATD LAG 1	.775	.972	.897	1.043	1.061	1.131	1.030
	LATD LAG 2	.100	-.086	-.065	-.174	-.228	-.177	-.001
	LATD LAG 3	-.013	.014	.067	.000	.111	.016	-.129
	LATD LAG 4	.128	-.029	.060	.078	.029	-.054	.110
	LATD LAG 5	-.183	.033	-.077	-.083	-.071	.014	-.170
	LOND LAG 1	-.111	-.017	-.215	-.134	-.060	-.060	-.032
	LOND LAG 2	.058	-.048	.107	.039	.045	.022	.096
	LOND LAG 3	-.013	.041	.038	.053	.021	.002	-.120
	LOND LAG 4	.016	.006	.009	.085	-.023	.060	.052
	LOND LAG 5	.032	.026	.029	-.065	.016	-.310	.006
	WS L1	.002	.001	.001	-.000	.000	.004	.004
	WS L2	-.003	-.001	-.002	.002	.004	-.003	.003
	WS L3	.002	-.002	.002	.001	-.003	-.004	.004
	WS L4	-.002	.003	-.001	-.003	-.002	.006	-.015
	WS L5	.001	-.001	.000	.001	.002	-.003	.007
STAT	R-SQR	.695	.738	.677	.806	.821	.805	.772
	MSE	.026	.033	.078	.061	.088	.119	.241
	# OBS	578	996	1344	1529	1256	1014	580

Table B.13. LOND Trivariate Coefficients (All Included)

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.100	.054	.039	-.057	-.076	-.095	-.169
	LATD LAG 1	.155	.083	-.401	.029	-.001	-.018	.193
	LATD LAG 2	-.053	-.082	.233	-.014	-.093	-.041	-.276
	LATD LAG 3	.045	-.060	.034	.030	.003	-.057	.176
	LATD LAG 4	-.160	.136	.004	-.151	.010	-.006	-.133
	LATD LAG 5	.066	-.035	.010	.043	-.026	.008	-.003
	LOND LAG 1	.859	.878	.617	1.055	1.089	1.233	1.083
	LOND LAG 2	-.031	-.068	.091	-.003	-.108	-.291	-.212
	LOND LAG 3	.121	.114	.105	-.148	-.065	.005	.182
	LOND LAG 4	.033	-.060	.058	.097	.070	.068	-.033
	LOND LAG 5	-.036	.072	.031	-.089	-.094	-.110	-.218
	WS L1	-.002	-.002	-.001	.000	.003	-.001	-.009
	WS L2	.001	-.002	.003	.002	-.004	.007	.007
	WS L3	.003	.003	-.000	-.002	.003	-.002	-.004
	WS L4	-.003	.002	-.001	-.001	.001	-.007	-.019
	WS L5	.000	-.001	.000	.002	-.001	.002	-.016
STAT	R-SQR	.840	.815	.625	.839	.865	.856	.796
	MSE	.045	.073	.216	.112	.133	.199	.493
	# OBS	578	996	1344	1529	1256	1014	580

Table B.14. LATD Trivariate Coefficients from Stepwise Procedure.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.068	.037	.078	.060	.019	.073	.001
	LATD LAG 1	.783	.971	.888	1.040	1.075	1.168	1.002
	LATD LAG 2	.099	-.075		-.172	-.241	-.211	
	LATD LAG 3					.134		
	LATD LAG 4	.166			.079			
	LATD LAG 5	-.176			-.085	-.056		-.148
	LOND LAG 1	-.109		-.208	-.114			
	LOND LAG 2	.058	-.063	.077				
	LOND LAG 3		.046	.061	.074			
	LOND LAG 4			.036	.085			
	LOND LAG 5	.037	.027		-.066			
	WS L1					.001		.007
	WS L2				.002			
	WS L3							
	WS L4				.001			-.010
	WS L5							.006
STAT	R-SQR	.693	.736	.674	.805	.820	.801	.768
	MSE	.025	.033	.077	.061	.088	.120	.241
	# OBS	578	996	1344	1529	1256	1014	580

Table B.15. LOND Trivariate Coefficients from Stepwise Procedure.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.094	.052	.061	-.046	-.048	-.094	-.183
	LATD LAG 1	.122		-.406				.198
	LATD LAG 2			.275		-.094	-.109	-.022
	LATD LAG 3							
	LATD LAG 4	-.089			-.080			
	LATD LAG 5							
	LOND LAG 1	.834	.864	.623	1.051	1.092	1.238	1.080
	LOND LAG 2			.077		-.129	-.295	-.200
	LOND LAG 3	.110		.124	-.149			.152
	LOND LAG 4			.075	.091		.075	
	LOND LAG 5		.067		-.079	-.067	-.111	-.230
	WS L1							-.005
	WS L2						.005	
	WS L3							
	WS L4	-.000					-.005	.018
	WS L5				.001			-.015
STAT	R-SQR	.838	.810	.624	.838	.864	.856	.795
	MSE	.045	.074	.215	.112	.132	.198	.491
	# OBS	578	996	1344	1529	1256	1014	580

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Table B.16. LATD Trivariate Coefficients from Backward Procedure.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.071	.034	.080	.060	.021	.071	.016
	LATD LAG 1	.775	.968	.876	1.040	1.064	1.149	.095
	LATD LAG 2	.094	-.072		-.172	-.230	-.208	
	LATD LAG 3					.129		
	LATD LAG 4	.115		.087	.079			
	LATD LAG 5	-.176		-.081	-.085	-.059		-.146
	LOND LAG 1	-.111		-.205	-.114	-.061	-.041	
	LOND LAG 2	.055	-.066	.078		.059		
	LOND LAG 3		.046	.064	.074			
	LOND LAG 4				.085		.043	
	LOND LAG 5	.038	.029	.030	-.066			
	WS L1	.002	.001					.006
	WS L2	-.002			.002	.001		
	WS L3		-.003		-.001			
	WS L4		.002					-.003
	WS L5							
STAT	R-SQR	.695	.737	.676	.805	.821	.803	.767
	MSE	.025	.033	.077	.061	.088	.119	.241
	# OBS	578	996	1344	1529	1256	1014	580

Table B.17. LOND Trivariate Coefficients from Backward Procedure.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.096	.052	.061	-.046	-.048	-.094	-.183
	LATD LAG 1	.131		-.406				.198
	LATD LAG 2		-.075	.275		-.094	-.109	-.225
	LATD LAG 3							
	LATD LAG 4	-.087	.075		-.080			
	LATD LAG 5							
	LOND LAG 1	.838	.866	.623	1.051	1.092	1.238	1.080
	LOND LAG 2			.077		-.129	-.295	-.200
	LOND LAG 3	.110		.124	-.149			.152
	LOND LAG 4			.075	.091		.075	
	LOND LAG 5		.070		-.079	-.067	-.111	-.230
	WS L1	-.002	-.003					-.005
	WS L2						.005	
	WS L3	.004	.003					
	WS L4	-.003					-.005	.018
	WS L5				.001			-.016
STAT	R-SQR	.839	.814	.624	.838	.864	.856	.795
	MSE	.045	.073	.215	.112	.132	.198	.491
	# OBS	578	996	1344	1529	1256	1014	580

Table B.18. Wind Speed Coefficients (All included).

		LATITUDE BANDS						
DEP	INDEP	10-15	15-20	20-25	25-30	30-35	35-40	40-45
WS	INTER-CEPT	.427	1.753	1.421	2.680	2.894	2.572	4.156
	LATD LAG 1	.904	.364	2.780	.643	.311	.148	-.076
	LATD LAG 2	1.813	-.389	-2.45	-.900	-.785	.010	.468
	LATD LAG 3	-1.46	.662	1.664	-.014	.330	.139	-.997
	LATD LAG 4	.243	-.210	-.328	.429	.144	-.817	.460
	LATD LAG 5	.555	.340	.286	-.344	-.285	.398	-.324
	LOND LAG 1	.204	.416	-.836	.301	.344	.160	.329
	LOND LAG 2	.572	-.730	.985	-.384	-.570	-.312	-.215
	LOND LAG 3	-.732	-.433	-.491	.539	-.055	.298	-.537
	LOND LAG 4	.728	-.572	.386	-.748	.231	.225	.733
	LOND LAG 5	.128	.098	-.108	.798	.509	-.232	-.316
	WS L1	1.470	1.430	1.424	1.414	1.342	1.355	1.167
	WS L2	-.446	-.401	-.481	-.413	-.249	-.249	-.110
	WS L3	-.069	-.011	.028	.029	-.140	-.147	-.191
	WS L4	.042	-.038	.001	-.127	.029	.016	.066
	WS L5	-.016	-.014	.003	.052	-.026	-.022	-.030
STAT	R-SQR	.973	.964	.957	.960	.970	.960	.924
	MSE	21.99	36.91	39.89	36.08	18.22	18.30	23.81
	# OBS	578	996	1344	1529	1256	1014	580

Table B.19. Wind Speed Coefficients (Stepwise & BackwarD).

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
WS	INTER-CEPT	.422	2.212	1.565	2.611	2.795	2.345	4.140
	LATD LAG 1			1.697				
	LATD LAG 2	2.032						
	LATD LAG 3							-.471
	LATD LAG 4							
	LATD LAG 5							
	LOND LAG 1							
	LOND LAG 2							
	LOND LAG 3							
	LOND LAG 4	.883						
	LOND LAG 5				.466	.447		
	WS L1	1.487	1.436	1.409	1.409	1.342	1.359	1.164
	WS L2	-.505	-.409	-.436	-.394	-.243	-.243	-.106
	WS L3					-.144	-.162	-.156
	WS L4		-.061		-.109			
	WS L5				.050			
STAT	R-SQR	.972	.963	.957	.960	.969	.960	.924
	MSE	21.71	36.63	39.76	35.94	18.14	18.20	23.56
	# OBS	578	996	1344	1529	1256	1014	580

Table B.20. LATD - FINAL Trivariate Coefficients.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LATD	INTER-CEPT	.065	.044	.091	.066	.019	.079	.029
	LATD LAG 1	.766	.954	.880	1.036	1.081	1.132	.996
	LATD LAG 2	.107	-.063		-.158	-.253	-.193	
	LATD LAG 3					.138		
	LATD LAG 4	.088		.075	.068	-.073		
	LATD LAG 5	-.143		-.087	-.079			-.137
	LOND LAG 1	-.105		-.206	-.114	-.053	-.057	
	LOND LAG 2	.054	-.034	.078				
	LOND LAG 3			.065	.098	.051		-.070
	LOND LAG 4						.129	.065
	LOND LAG 5	.038	.039	.030			-.066	
	WS L1	.002	.001			.001		
	WS L2	-.002						.007
	WS L3		-.001		.002			
	WS L4				-.002			-.005
	WS L5							
STAT	R-SQR	.690	.735	.691	.800	.820	.797	.762
	MSE	.025	.033	.079	.065	.087	.124	.239
	# OBS	659	1140	1467	1696	1346	1006	590

Table B.21. LOND - FINAL Trivariate Coefficients.

DEP	INDEP	LATITUDE BANDS
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
LOND	INTER-CEPT	.085	.049	.058	-.057	-.039	-.103	-.153
	LATD LAG 1	.136		-.383		-.049		.183
	LATD LAG 2			.251				-.208
	LATD LAG 3						-.129	
	LATD LAG 4	-.179			-.078			
	LATD LAG 5	.109				-.056		
	LOND LAG 1	.840	.855	.634	1.049	1.102	1.216	1.062
	LOND LAG 2			.093		-.073	-.246	-.152
	LOND LAG 3	.116		.119	-.142	-.081		.106
	LOND LAG 4			.065	.064			
	LOND LAG 5		.075		-.063	-.043	-.078	-.218
	WS L1	-.001						-.006
	WS L2		-.005		.001		.005	
	WS L3		.005					
	WS L4						-.005	.015
	WS L5							-.013
STAT	R-SQR	.840	.817	.647	.837	.863	.865	.799
	MSE	.046	.071	.206	.112	.137	.192	.479
	# OBS	659	1140	1467	1696	1346	1006	590

Table B.22. WS FINAL Trivariate Coefficients.

DEP	INDEP	LATITUDE BANDS						
		10-15	15-20	20-25	25-30	30-35	35-40	40-45
WS	INTER-CEPT	.586	2.116	1.617	2.748	2.825	2.380	4.300
	LATD LAG 1	1.457		1.529				
	LATD LAG 2							
	LATD LAG 3							
	LATD LAG 4	.622						
	LATD LAG 5							
	LOND LAG 1							
	LOND LAG 2							
	LOND LAG 3							
	LOND LAG 4							
	LOND LAG 5				.389	.422		
	WS L1	1.516	1.449	1.432	1.409	1.334	1.359	1.163
	WS L2	-.530	-.425	-.464	-.399	-.224	-.264	-.103
	WS L3					-.156	-.142	-.167
	WS L4		-.056		-.100			
	WS L5				.045			
STAT	R-SQR	.972	.965	.955	.960	.967	.957	.920
	MSE	21.43	35.21	40.67	34.53	18.41	18.70	23.43
	# OBS	659	1140	1467	1696	1346	1006	590

Table C.1. MEAN (STD) 6 Hour Forecast Summary Statistics on Test

```
WS MATRIX:  WS BACK (351 storms used in parameter estimation)

DATA:    MODEL BUILDING DATA BASE (351 storms)
```

```
6HR FORECAST
```

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7069.	17.0(24.4)	0.2(5.8)	0.1(0.3)	-0.1(0.4)
2.UNI FULL	7069.	14.1(22.5)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
3.UNI STEP	7069.	14.1(22.5)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
4.UNI BACK	7069.	14.1(22.5)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
5.BI FULL	7069.	14.0(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
6.BI STEP	7069.	14.4(22.3)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
7.BI BACK	7069.	14.2(22.2)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
8.TRI FULL	7069.	15.3(22.5)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
9.TRI STEP	7069.	15.0(22.2)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
10.TRI BACK	7069.	14.0(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
11.CURRY NEW	7069.	14.1(22.5)	-0.2(5.8)	0.0(0.3)	0.0(0.4)

Table C.2. MEAN (STD) 12 Hour Forecast Summary Statistics on Test

```
WS MATRIX:  WS BACK (351 storms used in parameter estimation)

DATA:    MODEL BUILDING DATA BASE (351 storms)
```

```
12HR FORECAST
```

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6735.	48.7(45.3)	-0.3(9.9)	0.2(0.7)	-0.3(1.0)
2.UNI FULL	6734.	42.2(39.9)	-0.3(9.8)	0.0(0.6)	0.0(0.9)
3.UNI STEP	6734.	42.3(40.0)	-0.3(9.8)	0.0(0.6)	0.0(0.9)
4.UNI BACK	6734.	42.3(39.9)	-0.3(9.8)	0.0(0.6)	0.0(0.9)
5.BI FULL	6734.	41.7(39.1)	-0.3(9.8)	0.0(0.6)	0.0(0.9)
6.BI STEP	6734.	42.9(39.8)	-0.3(9.8)	0.0(0.7)	0.0(0.9)
7.BI BACK	6734.	42.2(39.5)	-0.3(9.8)	0.0(0.6)	0.0(0.8)
8.TRI FULL	6735.	44.9(41.4)	-0.3(9.8)	-0.1(0.7)	0.0(0.8)
9.TRI STEP	6734.	44.4(39.4)	-0.3(9.3)	-0.1(0.7)	0.0(0.9)
10.TRI BACK	6734.	41.5(39.2)	-0.3(9.8)	0.0(0.6)	0.0(0.9)
11.CURRY NEW	6734.	41.9(40.0)	-0.3(9.8)	0.0(0.6)	0.0(0.9)

Table C.3. MEAN (STD) 24 Hour Forecast Summary Statistics on Test

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6083.	120.0(95.1)	-0.1(15.6)	0.5(1.6)	-0.7(2.3)
2.UNI FULL	6061.	106.0(80.5)	0.0(15.6)	0.0(1.4)	0.0(2.0)
3.UNI STEP	6060.	106.2(80.6)	0.0(15.6)	0.0(1.4)	0.0(2.0)
4.UNI BACK	6060.	106.1(80.5)	0.0(15.6)	0.0(1.4)	0.0(2.0)
5.BI FULL	6062.	104.6(78.2)	0.0(15.6)	-0.1(1.4)	0.0(2.0)
6.BI STEP	6060.	108.6(81.0)	0.0(15.6)	0.1(1.6)	0.0(2.0)
7.BI BACK	6061.	106.4(79.4)	0.0(15.5)	0.0(1.5)	0.0(2.0)
8.TRI FULL	6052.	113.6(88.3)	0.0(15.6)	-0.3(1.7)	-0.1(2.0)
9.TRI STEP	6063.	112.5(80.4)	-0.1(15.6)	-0.4(1.6)	-0.1(2.0)
10.TRI BACK	6065.	103.5(78.2)	0.0(15.6)	-0.1(1.4)	0.0(2.0)
11.CURRY NEW	6063.	105.0(80.4)	0.0(15.5)	-0.1(1.4)	0.0(2.0)

Table C.4. MEAN (STD) 48 Hour Forecast Summary Statistics Test

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4878.	269.8(196.4)	1.7(21.6)	1.2(3.2)	-1.7(5.1)
2.UNI FULL	4740.	250.0(170.6)	1.8(21.7)	-0.2(3.1)	0.1(4.8)
3.UNI STEP	4740.	250.3(169.0)	1.8(21.7)	-0.2(3.1)	0.2(4.7)
4.UNI BACK	4741.	250.5(170.4)	1.8(21.7)	-0.2(3.2)	0.1(4.8)
5.BI FULL	4745.	246.2(163.7)	1.8(21.7)	-0.3(3.1)	0.4(4.6)
6.BI STEP	4741.	259.1(177.6)	1.9(21.7)	0.1(3.6)	0.1(4.6)
7.BI BACK	4741.	253.3(172.7)	1.8(21.7)	0.0(3.4)	0.1(4.6)
8.TRI FULL	4550.	254.1(173.3)	2.0(21.9)	-0.3(3.5)	-0.1(4.5)
9.TRI STEP	4742.	267.9(173.3)	1.8(21.7)	-1.4(3.5)	0.3(4.6)
10.TRI BACK	4740.	242.2(163.7)	1.7(21.7)	-0.3(3.1)	0.1(4.5)
11.CURRY NEW	4738.	245.3(168.0)	1.8(21.7)	-0.3(3.1)	0.1(4.6)

Table C.5. MEA` TD) 72 Hour Forecast Summary Statistics Test

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	3881.	406.7(284.9)	3.4(24.2)	1.7(4.5)	-2.7(7.7)
2.UNI FULL	3642.	386.2(246.1)	3.7(24.6)	-0.6(4.6)	0.5(7.4)
3.UNI STEP	3638.	387.8(246.6)	3.6(24.6)	-0.5(4.6)	0.5(/.4)
4.UNI BACK	3638.	387.7(246.6)	3.6(24.6)	-0.5(4.6)	0.5(7.4)
5.BI FULL	3636.	380.2(237.3)	3.8(24.6)	-0.7(4.6)	0.9(7.0)
6.BI STEP	3636.	404.6(273.6)	3.9(24.6)	0.1(5.4)	0.3(7.3)
7.BI BACK	3641.	395.4(264.2)	3.7(24.6)	0.0(5.1)	0.3(7.2)
8.TRI FULL	3439.	383.3(242.5)	4.0(24.9)	-0.3(4.9)	-0.1(6.9)
9.TRI STEP	3596.	426.4(268.4)	4.5(24.7)	-2.6(5.2)	1.3(7.3)
10.TRI BACK	3648.	375.8(240.0)	3.7(24.6)	-0.6(4.6)	0.5(7.1)
11.CURRY NEW	3637.	378.8(241.4)	3.7(24.5)	-0.6(4.6)	0.5(7.1)

Table C.6. MSPR 6 Hour Forecast Summary Statistics on Model

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7069.	885.23	34.00	0.11	0.21
2.UNI FULL	7069.	705.33	34.00	0.09	0.17
3.UNI STEP	7069.	707.08	34.00	0.09	0.17
4.UNI BACK	7069.	706.04	34.00	0.09	0.17
5.BI FULL	7069.	686.10	34.00	0.08	0.16
6.BI STEP	7069.	707.29	34.00	0.09	0.16
7.BI BACK	7069.	695.96	34.00	0.09	0.16
8.TRI FULL	7069.	739.67	34.00	0.10	0.16
9.TRI STEP	7069.	717.54	34.00	0.09	0.16
10.TRI BACK	7069.	685.49	34.00	0.08	0.16
11.CURRY NEW	7069.	705.70	34.00	0.09	0.17

Table C.7. MSPR 12 Hour Forecast Summary Statistics on Model

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6735.	4419.33	97.17	0.54	1.00
2.UNI FULL	6734.	3372.48	96.91	0.41	0.75
3.UNI STEP	6734.	3384.61	96.93	0.41	0.75
4.UNI BACK	6734.	3379.43	96.92	0.41	0.75
5.BI FULL	6734.	3261.92	96.92	0.40	0.73
6.BI STEP	6734.	3424.98	96.95	0.44	0.72
7.BI BACK	6734.	3337.13	96.95	0.42	0.72
8.TRI FULL	6735.	3724.98	96.97	0.53	0.72
9.TRI STEP	6734.	3524.12	96.95	0.47	0.73
10.TRI BACK	6734.	3258.57	96.93	0.40	0.73
11.CURRY NEW	6734.	3355.13	96.91	0.40	0.75

Table C.8. MSPR 24 Hour Forecast Summary Statistics on Model

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6083.	23453.96	242.37	2.70	5.63
2.UNI FULL	6061.	17719.36	241.80	2.07	4.13
3.UNI STEP	6060.	17771.14	241.94	2.09	4.13
4.UNI BACK	6060.	17737.66	241.93	2.08	4.13
5.BI FULL	6062.	17043.48	241.81	2.02	3.92
6.BI STEP	6060.	18346.14	241.99	2.42	3.87
7.BI BACK	6061.	17624.23	241.76	2.23	3.86
8.TRI FULL	6052.	20703.30	242.00	3.11	3.83
9.TRI STEP	6063.	19133.20	241.95	2.67	3.84
10.TRI BACK	6065.	16838.73	241.77	2.02	3.84
11.CURRY NEW	6063.	17487.40	241.59	2.05	4.05

Table C.9. MSPR 48 Hour Forecast Summary Statistics on Model

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4878.	111336.02	467.29	11.60	28.38
2.UNI FULL	4740.	91587.85	473.45	9.92	22.68
3.UNI STEP	4740.	91186.86	473.78	9.95	22.44
4.UNI BACK	4741.	91748.20	473.90	10.00	22.61
5.BI FULL	4745.	87430.01	473.01	9.82	21.05
6.BI STEP	4741.	98658.22	473.86	12.78	21.17
7.BI BACK	4741.	93966.67	473.84	11.56	21.09
8.TRI FULL	4550.	94616.66	484.41	12.41	20.03
9.TRI STEP	4742.	101821.97	472.05	14.10	20.81
10.TRI BACK	4740.	85437.84	472.91	9.62	20.54
11.CURRY NEW	4738.	88371.16	473.29	9.81	21.46

Table C.10. MSPR 72 Hour Forecast Summary Statistics on Model

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: MODEL BUILDING DATA BASE (351 storms)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	3881.	246557.88	594.44	23.44	66.09
2.UNI FULL	3642.	209730.17	619.33	21.28	54.32
3.UNI STEP	3638.	211204.59	618.14	21.53	54.55
4.UNI BACK	3638.	211062.67	617.94	21.49	54.55
5.BI FULL	3636.	200811.08	619.01	21.22	50.31
6.BI STEP	3636.	238521.62	621.53	29.35	53.44
7.BI BACK	3641.	226068.36	618.58	26.51	52.63
8.TRI FULL	3439.	205692.69	636.55	24.34	47.00
9.TRI STEP	3596.	253823.28	631.58	34.06	54.53
10.TRI BACK	3648.	198780.30	616.60	21.12	49.96
11.CURRY NEW	3637.	201737.72	616.22	21.49	50.43

Table D.1. MEAN (STD) 6 Hour Forecast Statistics of Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	768.	18.6(22.9)	-0.5(5.5)	0.1(0.3)	-0.1(0.4)
2.UNI FULL	768.	15.6(21.7)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
3.UNI STEP	768.	15.7(21.5)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
4.UNI BACK	768.	15.8(21.6)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
5.BI FULL	768.	15.3(21.2)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
6.BI STEP	768.	15.6(21.6)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
7.BI BACK	768.	15.5(21.4)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
8.TRI FULL	768.	15.5(21.8)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
9.TRI STEP	768.	15.7(21.6)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
10.TRI BACK	768.	15.4(21.4)	-0.5(5.5)	0.0(0.3)	0.0(0.4)
11.CURRY NEW	768.	15.2(21.2)	-0.5(5.5)	0.0(0.3)	0.0(0.4)

Table D.2. MEAN (STD) 12 Hour Forecast Statistics of Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	727.	51.8(45.4)	-1.0(9.8)	0.2(0.8)	-0.3(1.0)
2.UNI FULL	727.	44.8(41.5)	-1.0(9.8)	0.0(0.7)	0.0(0.9)
3.UNI STEP	727.	44.7(41.5)	-1.0(9.8)	0.0(0.7)	0.0(0.9)
4.UNI BACK	727.	44.8(41.5)	-1.0(9.8)	0.0(0.7)	0.0(0.9)
5.BI FULL	727.	44.1(39.7)	-1.0(9.8)	0.0(0.7)	0.0(0.8)
6.BI STEP	727.	45.8(40.5)	-1.0(9.8)	0.0(0.7)	0.0(0.8)
7.BI BACK	727.	44.8(40.0)	-1.0(9.8)	0.0(0.7)	0.0(0.8)
8.TRI FULL	727.	45.1(41.1)	-1.0(9.8)	0.0(0.7)	0.0(0.8)
9.TRI STEP	727.	46.0(40.4)	-1.0(9.8)	-0.1(0.7)	-0.1(0.8)
10.TRI BACK	727.	44.3(39.7)	-1.0(9.8)	0.0(0.7)	0.0(0.8)
11.CURRY NEW	727.	44.2(39.6)	-1.0(9.8)	0.0(0.7)	0.0(0.8)

Table D.3. MEAN (STD) 24 Hour Forecast Statistics of Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	647.	128.7(106.8)	-1.5(15.8)	0.6(1.8)	-0.7(2.4)
2.UNI FULL	644.	116.4(97.5)	-1.6(15.9)	0.1(1.7)	-0.1(2.2)
3.UNI STEP	644.	116.3(97.7)	-1.6(15.9)	0.1(1.7)	-0.1(2.2)
4.UNI BACK	644.	116.4(97.6)	-1.6(15.9)	0.1(1.7)	-0.1(2.2)
5.BI FULL	644.	113.8(92.8)	-1.5(15.9)	0.0(1.7)	-0.1(2.1)
6.BI STEP	644.	118.5(95.6)	-1.5(15.9)	0.1(1.8)	-0.1(2.1)
7.BI BACK	644.	116.0(93.6)	-1.6(15.9)	0.1(1.7)	-0.1(2.1)
8.TRI FULL	644.	116.5(97.4)	-1.5(15.9)	0.1(1.8)	-0.1(2.1)
9.TRI STEP	644.	120.0(95.8)	-1.6(15.9)	-0.3(1.8)	-0.2(2.1)
10.TRI BACK	644.	113.8(93.0)	-1.5(15.9)	0.1(1.7)	-0.1(2.1)
11.CURRY NEW	644.	114.1(93.1)	-1.5(15.9)	0.1(1.7)	-0.1(2.1)

Table D.4. MEAN (STD) 48 Hour Forecast Statistics of Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	501.	287.1(227.0)	-1.8(19.3)	1.2(3.7)	-1.6(5.4)
2.UNI FULL	485.	270.9(212.4)	-2.1(19.7)	0.0(3.7)	-0.1(5.2)
3.UNI STEP	484.	270.1(210.1)	-2.1(19.7)	0.1(3.7)	-0.1(5.2)
4.UNI BACK	484.	270.3(210.3)	-2.1(19.7)	0.0(3.7)	-0.1(5.2)
5.BI FULL	486.	269.9(207.7)	-2.1(19.7)	-0.1(3.7)	-0.1(5.1)
6.BI STEP	484.	272.9(207.9)	-2.1(19.7)	0.0(3.9)	-0.2(5.1)
7.BI BACK	486.	271.5(208.2)	-2.0(19.7)	-0.1(3.8)	-0.2(5.0)
8.TRI FULL	481.	274.0(217.5)	-2.0(19.8)	0.1(4.0)	-0.4(5.0)
9.TRI STEP	486.	285.0(210.7)	-2.1(19.7)	-0.9(4.0)	-0.1(5.1)
10.TRI BACK	488.	267.6(206.3)	-2.0(19.7)	-0.1(3.8)	-0.2(5.0)
11.CURRY NEW	486.	270.7(206.7)	-2.0(19.7)	-0.1(3.7)	-0.2(5.1)

Table D.5. MEAN (STD) 72 Hour Forecast Statistics of Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	397.	409.8(326.3)	-2.4(20.6)	1.8(5.2)	-2.5(7.6)
2.UNI FULL	377.	416.7(310.5)	-2.9(21.0)	-0.3(5.5)	0.2(8.0)
3.UNI STEP	377.	416.2(310.3)	-2.8(21.0)	-0.1(5.5)	0.2(8.0)
4.UNI BACK	377.	417.1(310.9)	-2.8(21.0)	-0.2(5.5)	0.2(8.0)
5.BI FULL	378.	420.7(308.5)	-2.9(21.1)	-0.5(5.5)	0.1(8.1)
6.BI STEP	374.	417.6(315.4)	-2.9(21.2)	-0.2(5.7)	-0.2(8.0)
7.BI BACK	377.	419.7(317.6)	-2.8(21.1)	-0.4(5.6)	-0.1(8.1)
8.TRI FULL	362.	429.5(321.6)	-2.7(21.3)	0.0(6.1)	-0.9(7.8)
9.TRI STEP	375.	440.9(316.4)	-2 6(21.4)	-1.5(5.8)	0.1(8.2)
10.TRI BACK	377.	415.0(305.7)	-2.8(21.1)	-0.4(5.5)	0.0(7.9)
11.CURRY NEW	378.	424.5(311.5)	-2.8(21.1)	-0.3(5.6)	-0.1(8.2)

Table D.6. MSPR 6 Hour Forecast Statistics of the Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	768.	868.53	30.09	0.13	0.18
2.UNI FULL	768.	712.57	30.09	0.11	0.14
3.UNI STEP	768.	710.17	30.09	0.11	0.14
4.UNI BACK	768.	712.91	30.09	0.11	0.14
5.BI FULL	768.	682.70	30.09	0.10	0.14
6.BI STEP	768.	706.34	30.09	0.11	0.14
7.BI BACK	768.	695.38	30.09	0.11	0.14
8.TRI FULL	768.	715.37	30.09	0.11	0.14
9.TRI STEP	768.	714.24	30.09	0.11	0.14
10.TRI BACK	768.	695.54	30.09	0.10	0.14
11.CURRY NEW	768.	680.63	30.09	0.10	0.14

Table D.7. MSPR 12 Hour Forecast Statistics of the Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	727.	4738.33	96.27	0.62	1.00
2.UNI FULL	727.	3721.29	96.36	0.51	0.73
3.UNI STEP	727.	3719.94	96.44	0.51	0.73
4.UNI BACK	727.	3725.77	96.45	0.51	0.74
5.BI FULL	727.	3516.11	96.17	0.47	0.70
6.BI STEP	727.	3731.85	96.22	0.53	0.70
7.BI BACK	727.	3605.24	96.21	0.50	0.70
8.TRI FULL	727.	3716.70	96.35	0.52	0.71
9.TRI STEP	727.	3746.27	96.31	0.53	0.71
10.TRI BACK	727.	3532.88	96.18	0.47	0.71
11.CURRY NEW	727.	3520.84	96.18	0.46	0.71

Table D.8. MSPR 24 Hour Forecast Statistics of the Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	647.	27953.86	252.45	3.41	6.31
2.UNI FULL	644.	23035.03	254.82	3.00	4.77
3.UNI STEP	644.	23048.82	254.45	3.00	4.77
4.UNI BACK	644.	23050.85	254.50	3.00	4.77
5.BI FULL	644.	21545.08	254.26	2.78	4.49
6.BI STEP	644.	23167.71	253.87	3.27	4.45
7.BI BACK	644.	22214.30	254.49	3.00	4.46
8.TRI FULL	644.	23051.05	254.75	3.21	4.47
9.TRI STEP	644.	23559.33	254.29	3.36	4.48
10.TRI BACK	644.	21569.52	254.27	2.81	4.46
11.CURRY NEW	644.	21677.14	254.17	2.76	4.57

Table D.9. MSPR 48 Hour Forecast Statistics of the Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	501.	133809.02	375.54	15.01	32.05
2.UNI FULL	485.	118394.72	392.28	13.84	27.00
3.UNI STEP	484.	117027.34	391.32	13.43	27.03
4.UNI BACK	484.	117177.00	391.38	13.46	27.05
5.BI FULL	486.	115918.79	391.37	13.98	26.00
6.BI STEP	484.	117614.91	390.59	14.90	25.50
7.BI BACK	486.	116929.97	390.47	14.70	25.47
8.TRI FULL	481.	122253.40	394.09	16.21	25.03
9.TRI STEP	486.	125552.82	390.86	16.64	26.28
10.TRI BACK	488.	114066.02	389.80	14.06	25.16
11.CURRY NEW	486.	115928.04	390.05	13.78	26.21

Table D.10. MSPR 72 Hour Forecast Statistics of the Test Data Set

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: TEST DATA BASE (45 storms)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	397.	274112.28	427.93	30.45	64.59
2.UNI FULL	377.	269748.00	449.55	30.34	64.41
3.UNI STEP	377.	269224.75	447.18	30.19	64.38
4.UNI BACK	377.	270342.22	447.11	30.37	64.58
5.BI FULL	378.	271941.03	451.93	30.86	65.32
6.BI STEP	374.	273584.81	454.78	32.15	63.46
7.BI BACK	377.	276816.19	453.90	31.58	66.17
8.TRI FULL	362.	287606.34	458.87	36.98	61.45
9.TRI STEP	375.	294289.78	461.23	35.68	67.51
10.TRI BACK	377.	265396.12	450.27	30.61	62.72
11.CURRY NEW	378.	277001.84	451.27	31.04	66.90

Appendix E. Latitude Band Summary Statistics

Table E.1. Latitude Band Statistics for TRI BACK Model Building Data Set

Latitude Band (10-15N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	573.	6.7653	12.2422	0.1281	5.1500
12HR	560.	23.6436	21.9744	0.1112	9.1307
24HR	539.	62.2748	52.4679	-0.0477	16.0402
48HR	495.	151.9235	107.7578	-1.5302	25.7951
72HR	454.	248.9276	163.7661	-3.2511	30.2339

Latitude Band (15-20N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1093	9.697	26.8171	0.3991	6.7007
12HR	1064	31.340	39.4336	0.8182	11.5994
24HR	1008	77.606	56.8642	1.8014	18.4160
48HR	909	186.013	104.8636	2.0806	24.8898
72HR	820	300.984	166.7077	1.0684	27.4578

Latitude Band (20-25N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1325	11.749	18.7925	-0.0465	6.1376
12HR	1302	35.189	35.3651	-0.1479	10.8514
24HR	1253	87.757	69.1663	-0.7282	17.5982
48HR	1114	219.010	156.2066	-2.3232	23.4018
72HR	925	363.820	253.2657	-3.4279	25.5090

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Latitude Band (25-30N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1485.	12.5877	18.7460	0.3335	6.8726
12HR	1423.	39.9149	33.8797	0.4782	11.0966
24HR	1280.	106.4818	74.0642	-0.3750	16.1912
48HR	1028.	271.7776	171.0655	-4.0984	20.4844
72HR	783.	429.4855	245.1899	-8.0006	20.4054

Latitude Band (30-35N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	1212.	15.0224	19.9092	0.1173	4.5306
12HR	1176.	47.5794	37.4706	0.0962	7.4928
24HR	1108.	127.1264	81.7755	-0.1490	11.5852
48HR	825.	310.5803	173.2355	-2.0892	14.9582
72HR	519.	496.1300	244.4717	-4.7290	17.3825

Latitude Band (35-40N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	946.	20.4041	25.1931	0.2675	4.4091
12HR	900.	58.8302	47.9440	0.5432	7.2945
24HR	704.	140.3747	94.5617	0.1103	11. 1681
48HR	336.	320.4381	177.8245	-2.8090	15.9747
72HR	139.	526.7996	270.5906	-7.6553	18.3389

Latitude Band (40-45N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	435.	28.8181	27.5730	0.2811	5.3571
12HR	309.	68.3533	43.6306	0.3054	7.9838
24HR	173.	174.9660	86.8047	0.0670	11.5460
48HR	33.	495.5752	267.7177	2.6279	12.7545
72HR	8.	926.3521	245.4992	7.6454	12.4335

Table E.2. Latitude Band Statistics for TRI BACK Model Test Data Set

Latitude Band (10-15N degrees)

FORECAST	#OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	82.	5.9674	12.2625	0.0018	6.9753
12HR	80.	22.2019	21.6425	0.0473	12.9827
24HR	76.	54.4327	30.0039	-0.3189	22.3092
48HR	68.	118.5596	60.0564	0.5159	23.6850
72HR	64.	207.2246	123.3377	3.8483	21.7294

Latitude Band (15-20N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	142.	9.4401	15.4509	0.4973	4.9445
12HR	141.	29.4171	29.5486	1.3106	9.4029
24HR	141.	75.7104	55.3563	3.6633	17.9358
48HR	134.	190.4036	137.5752	6.4974	23.5444
72HR	118.	317.9708	268.9904	8.2312	27.3040

Latitude Band (20-25N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	118.	16.6161	19.0540	1.3386	6.1561
12HR	112.	47.8628	37.2701	2.9517	12.1397
24HR	98.	129.7444	99.8359	3.7788	17.3478
48HR	67.	343.8527	285.1470	2.5967	18.1608
72HR	43.	536.0518	412.4499	-2.6088	14.2447

Latitude Band (25-30N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	171.	17.5547	20.0380	0.3134	5.6981
12HR	164.	50.8185	39.5196	0.5613	10.1537
24HR	140.	136.3872	104.0475	0.1404	14.1743
48HR	95.	355.6502	239.7585	-2.2455	18.1464
72HR	61.	537.7274	292.3365	-3.2326	18.5527

Latitude Band (30-35N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	159.	16.5927	23.3355	0.6983	5.1365
12HR	150.	50.5033	47.6325	0.6613	6.8715
24HR	141.	137.2958	103.3371	1.2092	10.8538
48HR	109.	328.0773	168.2353	2.0904	12.5604
72HR	84.	557.3478	267.1497	2.7889	11.8182

Latitude Band (35-40N degrees)

FORECAST	# CBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	60.	21.5317	25.9186	-0.0128	3.8465
12HR	58.	59.2690	40.6763	-0.2109	6.2751
24HR	35.	135.0978	88.8907	-3.2292	9.7493
48HR	14.	283.3974	142.4806	-9.8549	5.8591
72HR	7.	429.2936	253.3595	-9.9094	11.5456

Latitude Band (40-45N degrees)

FORECAST	# OBS	MEAN	STDEV	WS MEAN	WS STDEV
6HR	36.	30.8428	35.9494	-0.1945	3.2955
12HR	22.	70.0513	39.1518	0.3533	4.6025
24HR	13.	196.4097	78.2726	4.3727	5.9167
48HR	1.	454.3116	NaN	16.1591	NaN
72HR	0.	NaN	NaN	NaN	NaN

Appendix F. Histograms

This Appendix contains frequency histograms of the great circle distance (GCD) forecast errors of the test set. The forecast model used was the TRI BACK model.
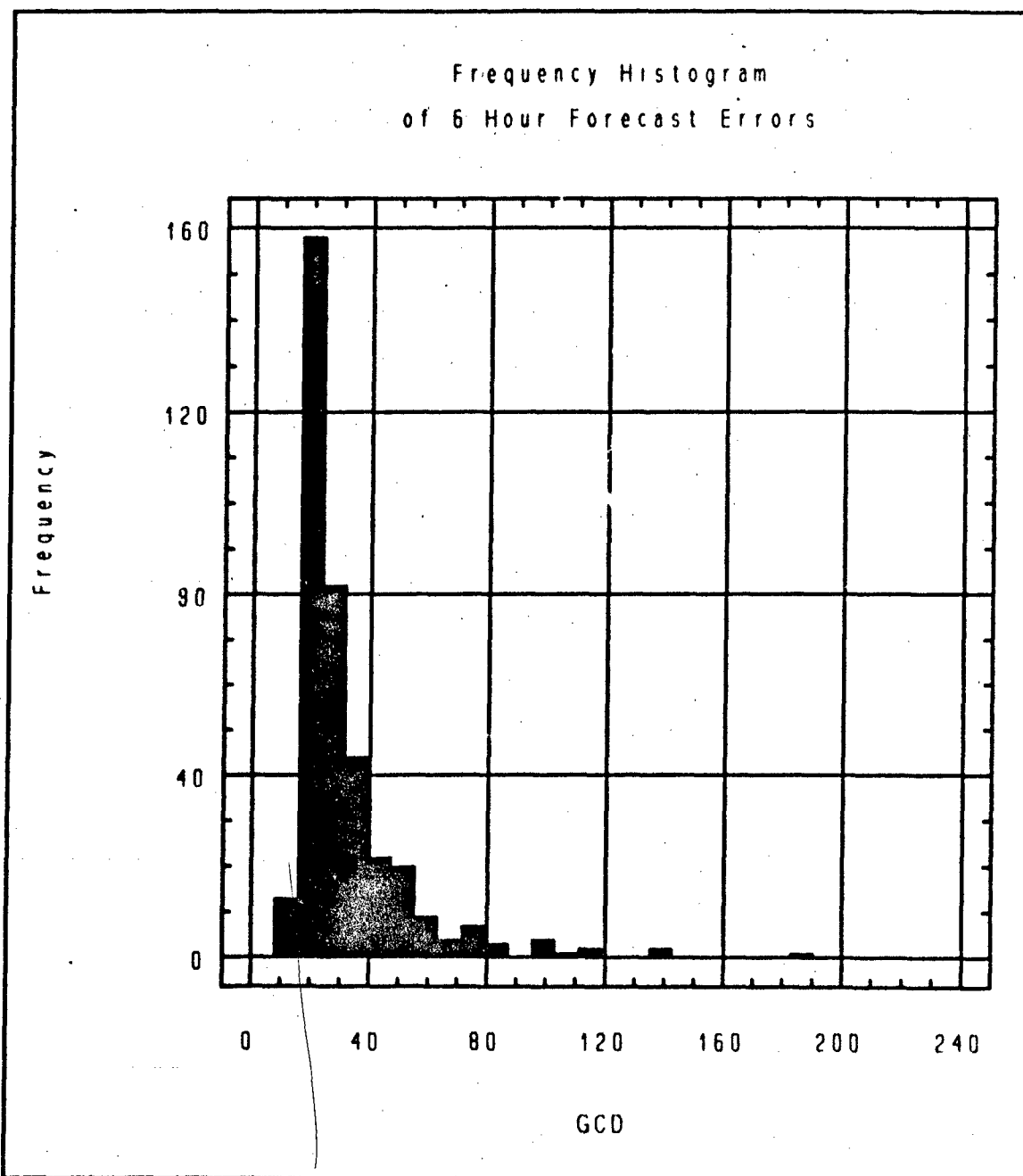
**Figure F.1.** Histogram of 6 Hour GCD Forecast Error for TRI BACK.
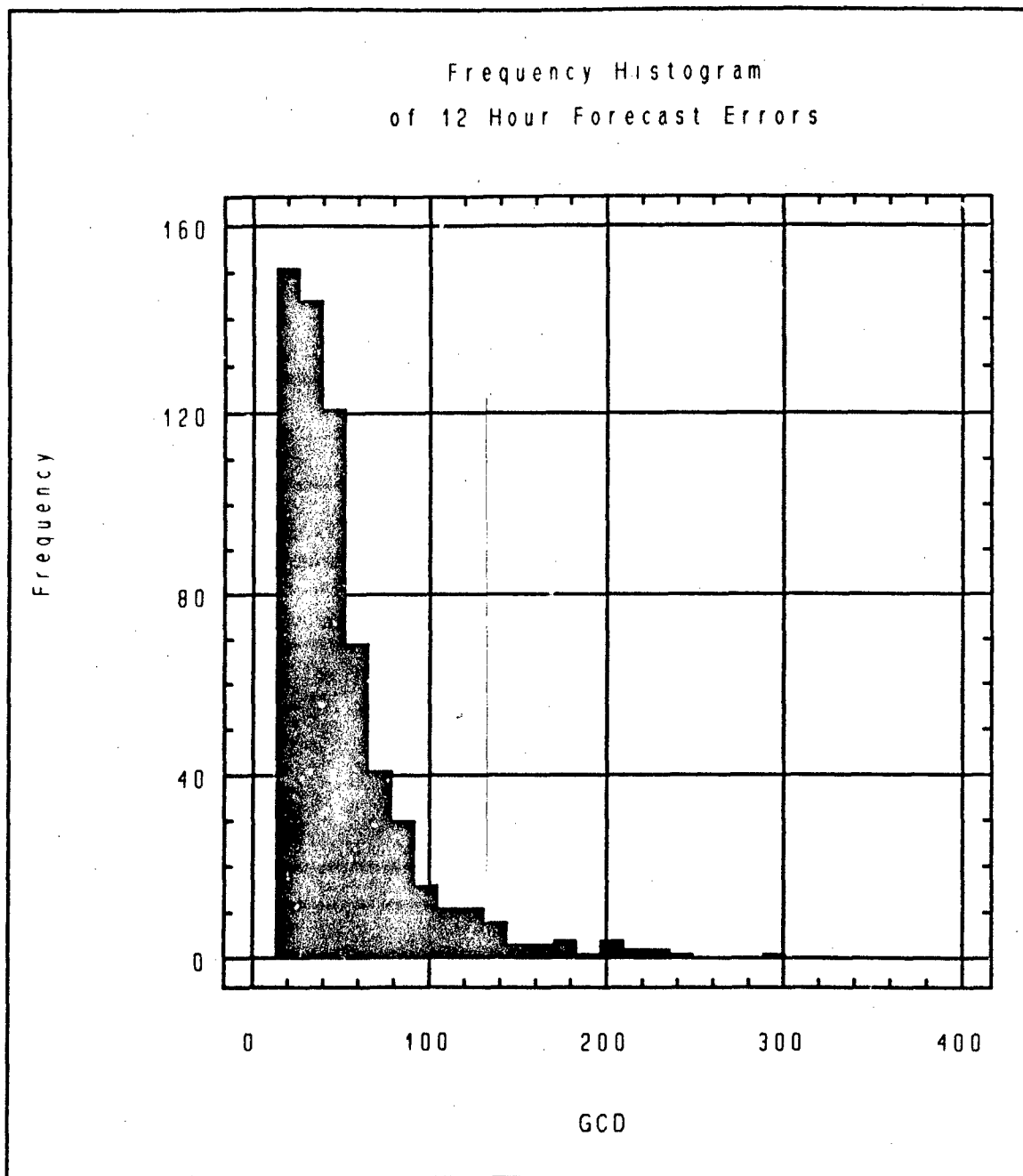
Figure F.2. Histogram of 12 Hour GCD Forecast Error for TRI BACK.
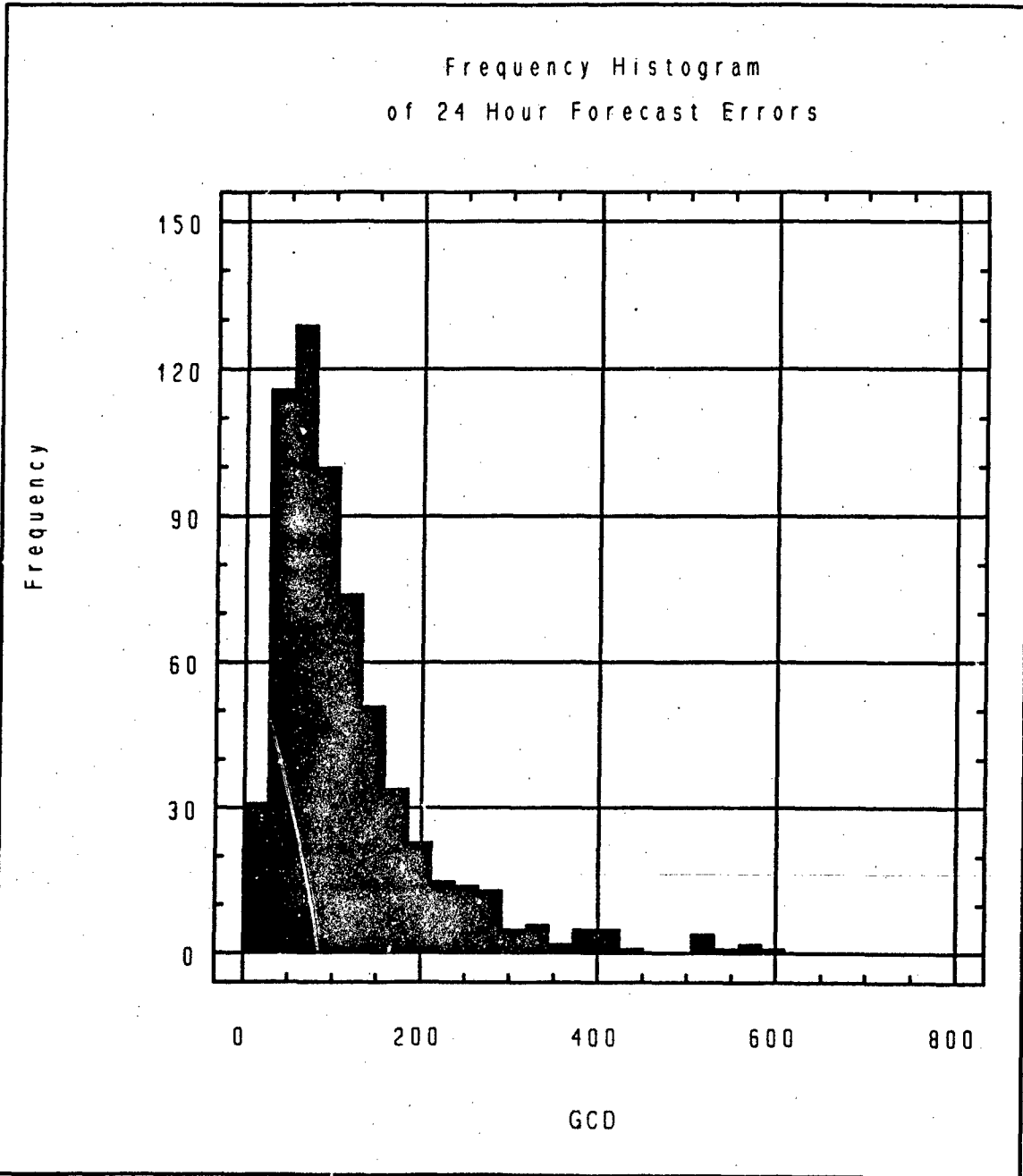
Figure F.3. Histogram of 24 Hour GCD Forecast Error for TRI BACK.
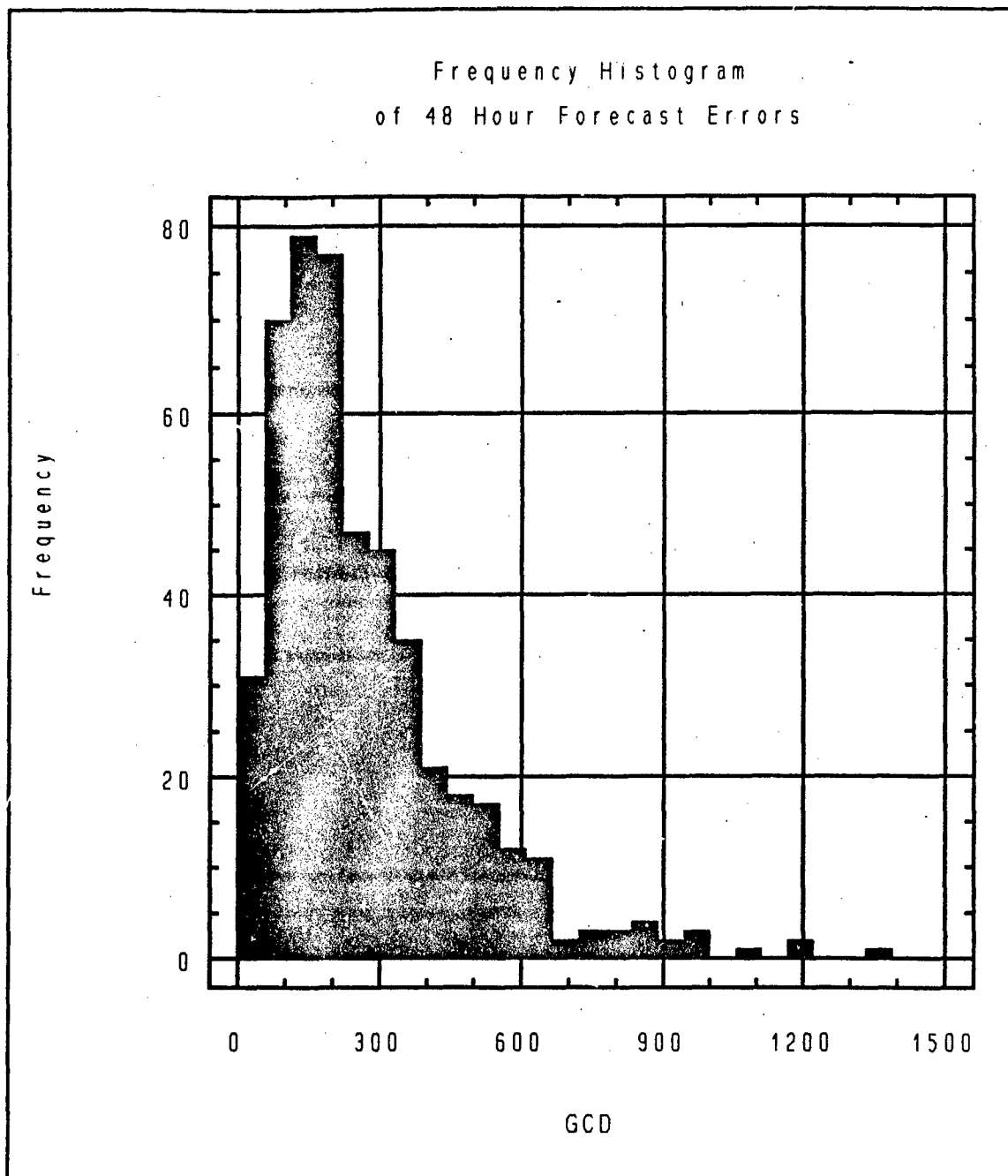
Figure F.4. Histogram of 48 Hour GCD Forecast Error for TRI BACK.

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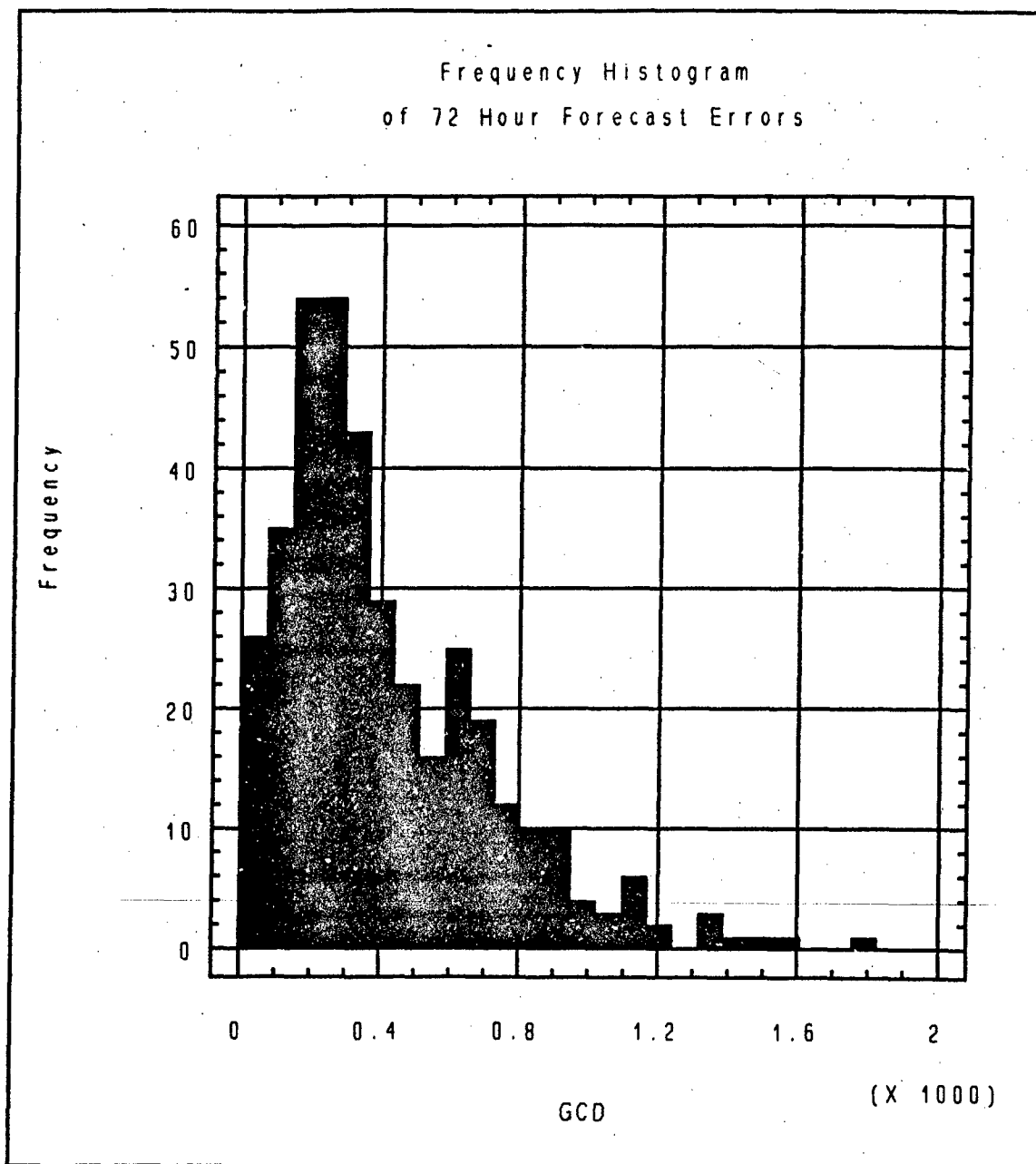
Figure F.5. Histogram of 72 Hour GCD Forecast Error for TRI BACK.

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Table G.1. Summary Statistics of Mean Squared Prediction Errors (MSPR)

WS MATRIX: WS BACK (351 storms used in parameter estimation)

DATA: ENTIRE DATA BASE (395 storms)

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7394.	879.82	33.50	0.11	0.21
2.TRI BACK	7394.	681.19	33.50	0.08	0.16
3.FINAL	7394.	678.05	33.50	0.08	0.16

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7038.	4408.62	95.57	0.54	1.00
2.TRI BACK	7037.	3247.12	95.34	0.40	0.72
3.FINAL	7037.	3238.82	95.34	0.40	0.71

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6344.	23367.53	238.73	2.71	5.57
2.TRI BACK	6326.	16781.12	238.18	2.03	3.80
3.FINAL	6324.	16754.41	238.30	2.03	3.79

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	5070.	110544.56	460.95	11.64	27.98
2.TRI BACK	4932.	85178.73	466.26	9.75	20.24
3.FINAL	4935.	85641.90	466.33	9.84	20.38

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4029.	244080.98	587.57	23.42	65.04
2.TRI BACK	3794.	198853.80	609.14	21.50	49.44
3.FINAL	3785.	199112.98	609.61	21.41	49.86

Table G.2. Summary Statistics of Mean Errors (Standard Deviations)

WS MATRIX: WS BACK (351 storms used in parameter estimation)
DATA: ENTIRE DATA BASE (395 storms)

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7394.	17.0(24.3)	-0.2(5.8)	0.1(0.3)	-0.1(0.4)
2.TRI BACK	7394.	14.0(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
3.FINAL	7394.	13.8(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7038.	48.7(45.2)	-0.4(9.8)	0.2(0.7)	-0.3(1.0)
2.TRI BACK	7037.	41.4(39.2)	-0.4(9.8)	0.0(0.6)	0.0(0.8)
3.FINAL	7037.	41.3(39.2)	-0.4(9.8)	0.0(0.6)	0.0(0.8)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6344.	119.8(94.9)	-0.2'15.5)	0.5(1.6)	-0.7(2.3)
2.TRI BACK	6326.	103.3(78.1)	-0.2(_5.4)	0.0(1.4)	0.0(1.9)
3.FINAL	6324.	103.3(77.9)	-0.2(15.4)	-0.1(1.4)	0.0(1.9)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	5070.	268.9(195.5)	1.3(21.4)	1.2(3.2)	-1.7(5.0)
2.TRI BACK	4932.	241.6(163.7)	1.4(21.5)	-0.3(3.1)	0.1(4.5)
3.FINAL	4935.	242.7(163.5)	1.4(21.6)	-0.3(3.1)	0.1(4.5)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4029.	404.6(283.6)	2.8(24.1)	1.7(4.5)	-2.7(7.6)
2.TRI BACK	3794.	375.5(240.6)	3.2(24.5)	-0.7(4.6)	0.5(7.0)
3.FINAL	3785.	376.1(240.2)	3.1(24.5)	-0.7(4.6)	0.4(7.0)

Table G.3. Summary Statistics of Mean Squared Prediction Errors (MSPR)

```
WS MATRIX:  WS FINAL (395 storms used in parameter estimation)
DATA:    ENTIRE DATA BASE (395 storms)
```

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7394.	879.82	33.51	0.11	0.21
2.TRI BACK	7394.	681.19	33.51	0.08	0.16
3.FINAL	7394.	678.05	33.51	0.08	0.16

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7038.	4408.62	95.55	0.54	1.00
2.TRI BACK	7037.	3247.01	95.35	0.40	0.72
3.FINAL	7037.	3238.83	95.36	0.40	0.71

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6344.	23367.53	239.11	2.71	5.57
2.TRI BACK	6325.	16774.70	238.56	2.03	3.80
3.FINAL	6324.	16752.35	238.61	2.03	3.79

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	5070.	110544.56	464.12	11.64	27.98
2.TRI BACK	4932.	85170.31	469.19	9.74	20.24
3.FINAL	4935.	85617.04	469.15	9.83	20.37

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4029.	244080.98	591.41	23.42	65.04
2.TRI BACK	3796.	198934.52	611.48	21.49	49.50
3.FINAL	3785.	199085.08	612.16	21.40	49.85

Table G.4. Summary Statistics of Mean Errors (Standard Deviations)

```
WS MATRIX:  WS FINAL (395 storms used in parameter estimation)
DATA:    ENTIRE DATA BASE (395 storms)
```

6HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7394.	17.0(24.3)	-0.2(5.8)	0.1(0.3)	-0.1(0.4)
2.TRI BACK	7394.	14.0(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)
3.FINAL	7394.	13.8(22.1)	-0.2(5.8)	0.0(0.3)	0.0(0.4)

12HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	7038.	48.7(45.2)	-0.3(9.8)	0.2(0.7)	-0.3(1.0)
2.TRI BACK	7037.	41.4(39.2)	-0.3(9.8)	0.0(0.6)	0.0(0.8)
3.FINAL	7037.	41.3(39.2)	-0.3(9.8)	0.0(0.6)	0.0(0.8)

24HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	6344.	119.8(94.9)	-0.1(15.5)	0.5(1.6)	-0.7(2.3)
2.TRI BACK	6325.	103.3(78.1)	-0.1(15.4)	0.0(1.4)	0.0(1.9)
3.FINAL	6324.	103.3(77.9)	-0.1(15.4)	-0.1(1.4)	0.0(1.9)

48HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	5070.	268.9(195.5)	1.6(21.5)	1.2(3.2)	-1.7(5.0)
2.TRI BACK	4932.	241.6(163.7)	1.6(21.6)	-0.3(3.1)	0.1(4.5)
3.FINAL	4935.	242.7(163.4)	1.6(21.6)	-0.3(3.1)	0.1(4.5)

72HR FORECAST

MODEL	#	DIST	WS	LAT	LON
1.CURRY	4029.	404.6(283.6)	3.1(24.1)	1.7(4.5)	-2.7(7.6)
2.TRI BACK	3796.	375.6(240.6)	3.5(24.5)	-0.7(4.6)	0.5(7.0)
3.FINAL	3785.	376.1(240.1)	3.4(24.5)	-0.7(4.6)	0.4(7.0)

Appendix H. FORTRAN for Forecasting Model

```
C****************************************************************
C  FORECASTING HURRICANE TRACKS IN DATA BASE FORM
C  Captain Timothy Mott
C
C  Date Last Modified:  6 February 1993
C
C  Purpose:  The purpose of this code is to forecast the
C  latitude, longitude and wind speeds of hurricane tracks up to
C  landfall.  The forecasts are made up to 72 hours.  The basic
C  structure of the program follows this outline
C
C     (1)   Read in hurricane data matrix
C     (2)   Set land fall boundary for data set
C     (3)   Read in model coefficients for position forecasting model
C     (4)   Read in model coefficients for wind speed forecasting
C           model
C     (5)   Make forecasting data matrix (lagged, present and
C           forecast value storage)
C     (6)   Forecast 6 hour position report
C     (7)   Repeat (6) 12 times to get 72 hour forecast
C     (8)   Calculate error statistics
C     (9)   Report error statistics
C    (10)   Report forecasts (6, 12, 24, 48, and 72 hour)
C
C  Important variables
C
C    N: The number of position reports in the data base
C    STM: the number of storms
C
C    BASE(15000,10): The data base of hurricane tracks
C        BASE(*,1): Hurricane storm ID
C        BASE(*,2): Report date
C        BASE(*,3): Report time
C        BASE(*,4): Report latitude
C        BASE(*,5): Report longitude
C        BASE(*,6): Report maximum sustained wind speed
C
C    BOUND: The East Coast landfall boundary line
C
C    FORE(15000,60): Each row contains the one through
C    six lag values, present value, and 12 forecasted values (6
C    through 72 hours) of latitude longitude and wind speed.
C    -999 is used to mark as a missing value
C
C    COEF(20,20): This is the matrix of position forecast
C    model coefficients
C
```

```
C     COEF2(20,20): This is the matrix of wind speed forecast
C     model coefficients
C
C     D6: The great circle distance (GCD)
C
C     TER(A,B): is the GCD forecast error of report A of the Bth
C     forecast
C
C     SUMERR(B,D): The sum of the position GCD forecast errors (D=1)
C                  The number of forecasts (D=2)
C                  The mean (D=3)
C                  The variance (D=4)
C                  The standard deviation (D=5)
C                  The sum of the squared error (D=6)
C
C     LAERR*(B,D): same as SUMERR but for latitude band (*)
C
C     WSERR(B,D): same as SUMERR but for wind speed
C
C     LWERR*(B,D): same as WSERR but for latitude band (*)
C
C******************************************************************

      program  FORECASTER

      INTEGER N, STM, ID
      INTEGER J, K, I, M,
      NEWST, COUNT

      REAL BASE(15000,10), FORE(15000,60)
      REAL COEF(20,20), COEF2(20,20)
      REAL LAERR1(7,7), LAERR2(7,7), LAERR3(7,7)
      REAL LAERR4(7,7), LAERR5(7,7)
      REAL LWERR1(7,7), LWERR2(7,7), LWERR3(7,7)
      REAL LWERR4(7,7), LWERR5(7,7), WSERR(5,6)
      REAL SUMERR(5,6), TER(15000,5), WER(15000,5)
      REAL PIR, D1, D2, D3, D4, D6, D7

      CHARACTER*20 NEWFL1, NEWFL2
      CHARACTER*20 NEWFL3, NEWFL4, NEWFL5
      CHARACTER*20 OLDFIL

      INTRINSIC ACOS, SIN, COS


C******************************************************************
C   GET THE HURRICANE TRACK DATA
C******************************************************************

      WRITE (*,001)
```

118

```
001     FORMAT(1X,'FILE NAME OF DATA FILE TO BE FORECASTED?')

        READ(*, '(A20)') OLDFIL

        OPEN(UNIT=23,FILE=OLDFIL,STATUS='OLD',IOSTAT=IERROR,ERR=100)

        WRITE(*,002)
002     FORMAT(1X,'FILE IS OPEN.')

        DO 10 N = 1, 10000, 1

            READ(23, *, END=20) BASE(N,1), BASE(N,2), BASE(N,3),
       + BASE(N,4), BASE(N,5), BASE(N,6)

10      CONTINUE

20      WRITE(*,21)
21      FORMAT(1X,'END OF FILE')

        CLOSE(23)

95      WRITE(*,96) N
96      FORMAT(1X,'THE NUMBER OF CASES IS :', I8)

        GO TO 120

100     WRITE(*,101) IERROR
101     FORMAT(' *** CANNOT OPEN FILE *** ', I8)

C ******  STORM COUNT ******

120        STM=1
           DO 380 K = 1,N,1
             BASE(K,7)=STM
             J=K+1
           IF((BASE(K,1).GT.0).AND.(BASE(K,1).NE.BASE(J,1)))STM=STM+1

380     CONTINUE

        WRITE(*,399) STM
399     FORMAT(1X,'THE NUMBER OF STORMS IS :', I8)

        WRITE(*,398) N
398     FORMAT(1X,'THE N IS :', I8)


C ***** THIS ASSUMES THAT THE DATA IS IN THE NO DECIMAL PLACE
C ***** FORMAT

        DO 1190 K = 1, N, 1
           BASE(K,4)=BASE(K,4)/10.0
```

119

```fortran
            BASE(K,5)=BASE(K,5)/10.0
1190    CONTINUE


C*******************************************************************
C    SET THE LANDFALL BOUNDARY
C*******************************************************************
        DO 1200 K = 1, N, 1
            BOUND = (-14.0/15.0)*BASE(K,5)-BASE(K,4)+110.33
            IF ((BASE(K,5).LE.70.0).AND.(BASE(K,4).LE.45.0))THEN
              BASE(K,7) = 0.0
             ELSE
              IF ((BASE(K,5).LE.80.0).AND.(BASE(K,5).GT.70.0).AND.
     +           (BOUND.GE.0.0))THEN
               BASE(K,7) = 0.0
              ELSE
                IF((BASE(K,5).LE.100.0).AND.(BASE(K,4).LE.31)) THEN
                  BASE(K,7) = 0.0
                ELSE
                   BASE(K,7) = 1.0
                ENDIF
              ENDIF
            ENDIF

1200    CONTINUE

        DO 1210 K = 1, N, 1
            L = K+1
            IF(BASE(L,1).EQ.BASE(K,1))THEN
              IF(BASE(K,7).EQ.1.0)THEN
                BASE(L,4) = -999
                BASE(L,5) = -999
               ELSE
                BASE(L,4)=BASE(L,4)
                BASE(L,5)=BASE(L,5)
              ENDIF
            ELSE
                BASE(L,4)=BASE(L,4)
                BASE(L,5)=BASE(L,5)
            ENDIF
1210    CONTINUE



C*******************************************************************
C GET THE MATRIX THAT HAS THE POSITION FORECASTING COEFFICIENTS
C*******************************************************************
        WRITE (*,501)
501     FORMAT(1X,'FILE NAME OF MATRX WITH THE FORECASTING
     +COEFFICIENTS?')
```

```
      READ(*, '(A20)') OLDFIL

      OPEN(UNIT=24,FILE=OLDFIL,STATUS='OLD',IOSTAT=IERROR,ERR=500)

      WRITE(*,502)
502   FORMAT(1X,'FILE IS OPEN.')

      DO 510 M = 1, 16, 1

          READ(24, *, END=520) COEF(M,1), COEF(M,2), COEF(M,3),
     +  COEF(M,4), COEF(M,5), COEF(M,6), COEF(M,7), COEF(M,8),
     +  COEF(M,9), COEF(M,10), COEF(M,11), COEF(M,12), COEF(M,13),
     +  COEF(M,14)

510      CONTINUE

520      WRITE(*,521)
521      FORMAT(1X,'END OF FILE')

      CLOSE(24)

      GO TO 900

500      WRITE(*,507)IERROR
507      FORMAT('*** CANNOT OPEN FILE ***',I8)


C*****************************************************************
C GET THE MATRIX THAT HAS THE WIND SPEED FORECASTING COEFFICIENTS
C*****************************************************************
900      WRITE (*,901)
901      FORMAT(1X,'FILE NAME OF MATRX WITH THE WS COEFFICIENTS?')

      READ(*, '(A20)') OLDFIL

      OPEN(UNIT=44,FILE=OLDFIL,STATUS='OLD',IOSTAT=IERROR,ERR=999)

      WRITE(*,902)
902      FORMAT(1X,'FILE IS OPEN.')

      DO 910 M = 1, 16, 1

          READ(44, *, END=520) COEF2(M,1), COEF2(M,2), COEF2(M,3),
     +  COEF2(M,4), COEF2(M,5), COEF2(M,6), COEF2(M,7)

910      CONTINUE

920      WRITE(*,921)
921      FORMAT(1X,'END OF FILE')

      CLOSE(44)
```

```
          GO TO 922

999    WRITE(*,907)IERROR
907    FORMAT('*** CANNOT OPEN WS FILE ***',I8)



C*********************************************************************
C   BUILD THE FORECAST MATRIX
C*********************************************************************
922       DO 400 I=1, N, 1
            DO 410 J=1, 60, 1
                   FORE(I,J)=-999
410        CONTINUE
400    CONTINUE


C ***** PUT PRESENT VALUES INTO FORECAST MATRIX
         DO 430 I=1,N,1
            FORE(I,20)=BASE(I,1)
            FORE(I,7)=BASE(I,4)
            FORE(I,27)=BASE(I,5)
            FORE(I,47)=BASE(I,6)
430       CONTINUE
C ***** LAG 1
      ID = FORE(1,20)
            DO 440 I=2,N,1
            IF(FORE(I,20).EQ.ID)THEN
                   FORE(I,6)=BASE(I-1,4)
               FORE(I,26)=BASE(I-1,5)
               FORE(I,46)=BASE(I-1,6)
            ELSE
               ID = FORE(I,20)
            ENDIF
440   CONTINUE
C ***** LAG 2
      ID = FORE(2,20)
      COUNT = 0
      DO 450 I=1,N,1
            IF(FORE(I,20).EQ.ID)THEN
                   IF (COUNT.LT.2)THEN
                      COUNT = COUNT+1
                    ELSE
                      FORE(I,5)=BASE(I-2,4)
                 FORE(I,25)=BASE(I-2,5)
                 FORE(I,45)=BASE(I-2,6)
                    ENDIF
            ELSE
               ID = FORE(I,20)
                    COUNT=1
            ENDIF
450   CONTINUE


                              122
```

```
C ***** LAG 3
      ID = FORE(3,20)
        COUNT=0
      DO 460 I=1,N,1
          IF(FORE(I,20).EQ.ID)THEN
              IF (COUNT.LT.3)THEN
                     COUNT = COUNT+1
                  ELSE
                     FORE(I,4)=BASE(I-3,4)
                 FORE(I,24)=BASE(I-3,5)
                 FORE(I,44)=BASE(I-3,6)
                    ENDIF
          ELSE
             ID = FORE(I,20)
                  COUNT=1
          ENDIF
460   CONTINUE

C ***** LAG 4
      ID = FORE(4,20)
        COUNT = 0
      DO 470 I=1,N,1
          IF(FORE(I,20).EQ.ID)THEN
              IF (COUNT.LT.4)THEN
                     COUNT = COUNT+1
                  ELSE
                     FORE(I,3)=BASE(I-4,4)
                 FORE(I,23)=BASE(I-4,5)
                 FORE(I,43)=BASE(I-4,6)
                    ENDIF
          ELSE
              ID = FORE(I,20)
                  COUNT=1
          ENDIF
470   CONTINUE
C ***** LAG 5
      ID = FORE(5,20)
        COUNT=0
      DO 480 I=1,N,1
          IF(FORE(I,20).EQ.ID)THEN
              IF (COUNT.LT.5)THEN
                     COUNT = COUNT+1
                  ELSE
                     FORE(I,2)=BASE(I-5,4)
                 FORE(I,22)=BASE(I-5,5)
                 FORE(I,42)=BASE(I-5,6)
                    ENDIF
          ELSE
             ID = FORE(I,20)
                  COUNT=1
          ENDIF
```

```
 480   CONTINUE
C *****  LAG 6
       ID = FORE(6,20)
          COUNT=0
       DO 490 I=7,N,1
            IF(FORE(I,20).EQ.ID)THEN
              IF (COUNT.LT.6)THEN
                    COUNT = COUNT+1
                  ELSE
                    FORE(I,1)=BASE(I-6,4)
                FORE(I,21)=BASE(I-6,5)
                FORE(I,41)=BASE(I-6,6)
                   ENDIF
            ELSE
               ID = FORE(I,20)
            ENDIF
 490   CONTINUE




C********************************************************************
C   FORECAST USING THE POSITION AND WS COEFFICIENTS
C   THIS IS REPEATED FOR 12 FORECASTS (6 THROUGH 72 HOURS)
C********************************************************************

     ID = 0
     NEWST = 0

     DO 550 I=1,N,1

C *****   SKIP FIRST SIX OBS OF A STORM -- TO HAVE ENOUGH INFO
C *****   TO FORECAST

       IF(FORE(I,20).EQ.ID)THEN
         NEWST=NEWST+1
        ELSE
           ID = FORE(I,20)
           NEWST=1
        ENDIF

C ***** DO NOT FORECAST IF OUT OF RANGE

       IF(NEWST.LT.7)GO TO 550


C ***** DO FORECASTS 6 THROUGH 72 HOURS

     DO 560 J=1,12,1

C ***** SKIP FORECAST IF THE TIME AHEAD IS NOT IN DATA
```

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```
C ***** THIS IS DONE BECAUSE OTHERWISE THERE WOULD BE NO
C ***** WAY TO CHECK ACCURACY OF FORECAST

      IF(FORE(I+J,20).NE.FORE(I,20))GO TO 560


C *****  SKIP FORECAST IF INFO USED IS NONEXSISTENT
      FLAG=0
      DO 561 K=1,7,1
       IF((FORE(I,7+J-K).LT.0).OR.(FORE(I,27+J-K).LT.0))FLAG=1
561   CONTINUE
       IF(FLAG.EQ.1)GO TO 560


C ***** GET PROPER LATITUDE BAND FOR FORECAST MODEL
        K=0
      IF(FORE(I,6+J).LT.15.0)K=1
      IF((FORE(I,6+J).LT.20.0).AND.(FORE(I,6+J).GE.15.0))K=2
      IF((FORE(I,6+J).LT.25.0).AND.(FORE(I,6+J).GE.20.0))K=3
      IF((FORE(I,6+J).LT.30.0).AND.(FORE(I,6+J).GE.25.0))K=4
      IF((FORE(I,6+J).LT.35.0).AND.(FORE(I,6+J).GE.30.0))K=5
      IF((FORE(I,6+J).LT.40.0).AND.(FORE(I,6+J).GE.35.0))K=6
      IF((FORE(I,6+J).LE.45.0).AND.(FORE(I,6+J).GE.40.0))K=7
      IF(K.EQ.0)THEN
           FORE(I,7+J)=-999
           FORE(I,27+J)=-999
        GO TO 560
      ENDIF

C  *****  FORECAST  LATITUDE  USING  INPUTTED  FORECAST  MODEL
COEFFICIENTS

      FORE(I,7+J)=FORE(I,6+J)
     ++COEF(1,K)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF(2,K)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF(3,K)*(FORE(I,4+J)-FORE(I,3+J))
     ++COEF(4,K)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF(5,K)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF(6,K)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF(7,K)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF(8,K)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF(9,K)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF(10,K)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF(11,K)*(FORE(I,46+J))
     ++COEF(12,K)*(FORE(I,45+J))
     ++COEF(13,K)*(FORE(I,44+J))
     ++COEF(14,K)*(FORE(I,43+J))
     ++COEF(15,K)*(FORE(I,42+J))
     ++COEF(16,K)
```

```fortran
C  *****  FORECAST  LONGITUDE  USING  INPUTTED  FORECAST  MODEL
COEFFICIENTS

      FORE(I,27+J)=FORE(I,26+J)              .
     ++COEF(1,K+7)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF(2,K+7)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF(3,K+7)*(FORE(I,4+J)-FORE(I,3+J))
     ++COEF(4,K+7)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF(5,K+7)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF(6,K+7)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF(7,K+7)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF(8,K+7)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF(9,K+7)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF(10,K+7)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF(11,K+7)*(FORE(I,46+J))
     ++COEF(12,K+7)*(FORE(I,45+J))
     ++COEF(13,K+7)*(FORE(I,44+J))
     ++COEF(14,K+7)*(FORE(I,43+J))
     ++COEF(15,K+7)*(FORE(I,42+J))
     ++COEF(16,K+7)

C  *****  FORECAST  WIND  SPEED  USING  INPUTTED  FORECAST  MODEL
COEFFICIENTS
      FORE(I,47+J)=COEF2(1,K)*(FORE(I,6+J)-FORE(I,5+J))
     ++COEF2(2,K)*(FORE(I,5+J)-FORE(I,4+J))
     ++COEF2(3,K)*(FORE(I,4+J)-FORE(I,3+J))
     ++COEF2(4,K)*(FORE(I,3+J)-FORE(I,2+J))
     ++COEF2(5,K)*(FORE(I,2+J)-FORE(I,1+J))
     ++COEF2(6,K)*(FORE(I,26+J)-FORE(I,25+J))
     ++COEF2(7,K)*(FORE(I,25+J)-FORE(I,24+J))
     ++COEF2(8,K)*(FORE(I,24+J)-FORE(I,23+J))
     ++COEF2(9,K)*(FORE(I,23+J)-FORE(I,22+J))
     ++COEF2(10,K)*(FORE(I,22+J)-FORE(I,21+J))
     ++COEF2(11,K)*(FORE(I,46+J))
     ++COEF2(12,K)*(FORE(I,45+J))
     ++COEF2(13,K)*(FORE(I,44+J))
     ++COEF2(14,K)*(FORE(I,43+J))
     ++COEF2(15,K)*(FORE(I,42+J))
     ++COEF2(16,K)
560   CONTINUE
550   CONTINUE


C******************************************************************
C GETTING STATISTICS ON THE FORECAST ERRORS
C******************************************************************
      ID = 0
      DO 600 I=1,N,1
C  *****  SET FIRST SIX TO -999
      IF(FORE(I,20).EQ.ID)THEN
         NEWST=NEWST+1
```

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```
          ELSE
              ID = FORE(I,20)
              NEWST=1
          ENDIF

          IF(NEWST.LT.7)THEN
              TER(I,1)=-999
              TER(I,2)=-999
              TER(I,3)=-999
              TER(I,4)=-999
              TER(I,5)=-999
              GO TO 600
          ENDIF

C ***** DO NOT GET FORECAST ERROR IF OUT OF RANGE

          IF(FORE(I,7).GT.45.0)THEN
              TER(I,1)=-999
              TER(I,2)=-999
              TER(I,3)=-999
              TER(I,4)=-999
              TER(I,5)=-999
              GO TO 600
          ENDIFC ***** CHOOSE PROPER FORECAST MODEL
        K=0
    IF(FORE(I,7).LT.15.0)K=1
        IF((FORE(I,7).LT.20.0).AND.(FORE(I,7).GE.15.0))K=2
        IF((FORE(I,7).LT.25.0).AND.(FORE(I,7).GE.20.0))K=3
        IF((FORE(I,7).LT.30.0).AND.(FORE(I,7).GE.25.0))K=4
        IF((FORE(I,7).LT.35.0).AND.(FORE(I,7).GE.30.0))K=5
        IF((FORE(I,7).LT.40.0).AND.(FORE(I,7).GE.35.0))K=6
        IF((FORE(I,7).LE.45.0).AND.(FORE(I,7).GE.40.0))K=7
        IF(K.EQ.0)THEN
              TER(I,1)=-999
              TER(I,2)=-999
              TER(I,3)=-999
              TER(I,4)=-999
              TER(I,5)=-999
              GO TO 600
          ENDIF


      PIR = 180.0/(ACOS(-1.00))


C **** 6 HOUR FORECAST ERROR

      IF((FORE(I,20).EQ.FORE(I+1,20)).AND.(FORE(I,8).GE.0.0)
     +.AND.(FORE(I+1,7).GE.0.0).AND.(FORE(I,28).GT.0.0).AND.
     +(FORE(I+1,27).GT.0.0))THEN
```

```
C *****    GREAT CIRCLE DISTANCE BETWEEN ACTUAL AND FORECASTED

          D1=SIN(FORE(I,8)/PIR)
          D3=SIN(FORE(I+1,7)/PIR)
          D2=COS(FORE(I,8)/PIR)
          D4=COS(FORE(I+1,7)/PIR)
          D6=COS((FORE(I+1,27)-FORE(I,28))/PIR)

          IF((D1*D3+D2*D4*D6).GE.0.99999)THEN
            D7=0.0
           ELSE
            D7=ACOS(D1*D3+D2*D4*D6)
           ENDIF
          TER(I,1) = (D7*PIR)*60.0

             SUMERR(1,1)=SUMERR(1,1)+TER(I,1)
             SUMERR(1,2)=SUMERR(1,2)+1
             SUMERR(1,6)=TER(I,1)*TER(I,1)+SUMERR(1,6)

             LAERR1(K,1)=LAERR1(K,1)+TER(I,1)
             LAERR1(K,2)=LAERR1(K,2)+1
             LAERR1(K,7)=TER(I,1)*TER(I,1)+LAERR1(K,7)

             WER(I,1) =   (FORE(I,48)-FORE(I+1,47))
             WSERR(1,1)=WSERR(1,1)+WER(I,1)
             WSERR(1,2)=WSERR(1,2)+1
             WSERR(1,6)=WER(I,1)*WER(I,1)+WSERR(1,6)

             LWERR1(K,1)=LWERR1(K,1)+WER(I,1)
             LWERR1(K,2)=LWERR1(K,2)+1
             LWERR1(K,7)=WER(I,1)*WER(I,1)+LWERR1(K,7)

            ELSE
              TER(I,1)=-999
              WER(I,1)=-999
          ENDIF

C ****  12 HOUR FORECAST ERROR

          IF((FORE(I,20).EQ.FORE(I+2,20)).AND.(FORE(I,9).GE.0.0)
         +.AND.(FORE(I+2,7).GE.0.0).AND.(FORE(I,29).GT.0.0).AND.
         +(FORE(I+2,27).GT.0.0))THEN

C *****    GREAT CIRCLE DISTANCE BETWEEN ACTUAL AND FORECASTED

          D1=(SIN(FORE(I,9)/PIR))
          D3=(SIN(FORE(I+2,7)/PIR))
          D2=(COS(FORE(I,9)/PIR))
          D4=(COS(FORE(I+2,7)/PIR))
          D6=(COS((FORE(I+2,27)-FORE(I,29))/PIR))
```

```
          IF((D1*D3+D2*D4*D6).GE.0.99999)THEN
            D7=0.0
          ELSE
            D7=ACOS(D1*D3+D2*D4*D6)
          ENDIF

          TER(I,2) = (D7*PIR)*60.0

            SUMERR(2,1)=SUMERR(2,1)+TER(I,2)
            SUMERR(2,2)=SUMERR(2,2)+1
            SUMERR(2,6)=TER(I,2)*TER(I,2)+SUMERR(2,6)

            LAERR2(K,1)=LAERR2(K,1)+TER(I,2)
            LAERR2(K,2)=LAERR2(K,2)+1
            LAERR2(K,7)=TER(I,2)*TER(I,2)+LAERR2(K,7)

            WER(I,2) = (FORE(I,49)-FORE(I+2,47))
            WSERR(2,1)=WSERR(2,1)+WER(I,2)
            WSERR(2,2)=WSERR(2,2)+1
            WSERR(2,6)=WER(I,2)*WER(I,2)+WSERR(2,6)

            LWERR2(K,1)=LWERR2(K,1)+WER(I,2)
            LWERR2(K,2)=LWERR2(K,2)+1
            LWERR2(K,7)=WER(I,2)*WER(I,2)+LWERR2(K,7)

          ELSE
            TER(I,2)=-999
            WER(I,2)=-999
        ENDIF

C **** 24 HOUR FORECAST ERROR

      IF((FORE(I,20).EQ.FORE(I+4,20)).AND.(FORE(I,11).GE.0.0)
     +.AND.(FORE(I+4,7).GE.0.0).AND.(FORE(I,31).GT.0.0).AND.
     +(FORE(I+4,27).GT.0.0))THEN

C *****  GREAT CIRCLE DISTANCE BETWEEN ACTUAL AND FORECASTED

          D1=(SIN(FORE(I,11)/PIR))
          D3=(SIN(FORE(I+4,7)/PIR))
          D2=(COS(FORE(I,11)/PIR))
          D4=(COS(FORE(I+4,7)/PIR))
          D6=(COS((FORE(I+4,27)-FORE(I,31))/PIR))

          IF((D1*D3+D2*D4*D6).GE.0.99999)THEN
            D7=0.0
          ELSE
            D7=ACOS(D1*D3+D2*D4*D6)
          ENDIF
```

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```
      TER(I,3) = (D7*PIR)*60.0

          SUMERR(3,1)=SUMERR(3,1)+TER(I,3)
          SUMERR(3,2)=SUMERR(3,2)+1
        . SUMERR(3,6)=TER(I,3)*TER(I,3)+SUMERR(3,6)

          LAERR3(K,1)=LAERR3(K,1)+TER(I,3)
          LAERR3(K,2)=LAERR3(K,2)+1
          LAERR3(K,7)=TER(I,3)*TER(I,3)+LAERR3(K,7)

          WER(I,3) =   (FORE(I,51)-FORE(I+4,47))
          WSERR(3,1)=WSERR(3,1)+WER(I,3)
          WSERR(3,2)=WSERR(3,2)+1
          WSERR(3,6)=WER(I,3)*WER(I,3)+WSERR(3,6)

          LWERR3(K,1)=LWERR3(K,1)+WER(I,3)
          LWERR3(K,2)=LWERR3(K,2)+1
          LWERR3(K,7)=WER(I,3)*WER(I,3)+LWERR3(K,7)

        ELSE
         TER(I,3)=-999
         WER(I,3)=-999
      ENDIF

C **** 48 HOUR FORECAST ERROR

      IF((FORE(I,20).EQ.FORE(I+8,20)).AND.(FORE(I,15).GE.0.0)
     +.AND.(FORE(I+8,7).GE.0.0).AND.(FORE(I,25).GT.0.0).AND.
     +(FORE(I+8,27).GT.0.0))THEN

C *****  GREAT CIRCLE DISTANCE BETWEEN ACTUAL AND FORECASTED

          D1=(SIN(FORE(I,15)/PIR))
          D3=(SIN(FORE(I+8,7)/PIR))
          D2=(COS(FORE(I,15)/PIR))
          D4=(COS(FORE(I+8,7)/PIR))
          D6=(COS((FORE(I+8,27)-FORE(I,35))/PIR))

       IF((D1*D3+D2*D4*D6).GE.0.99999)THEN
           D7=0.0
          ELSE
           D7=ACOS(D1*D3+D2*D4*D6)
          ENDIF

       TER(I,4) = (D7*PIR)*60.0

          SUMERR(4,1)=SUMERR(4,1)+TER(I,4)
          SUMERR(4,2)=SUMERR(4,2)+1
          SUMERR(4,6)=TER(I,4)*TER(I,4)+SUMERR(4,6)
```

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```fortran
            LAERR4(K,1)=LAERR4(K,1)+TER(I,4)
            LAERR4(K,2)=LAERR4(K,2)+1
            LAERR4(K,7)=TER(I,4)*TER(I,4)+LAERR4(K,7)

            WER(I,4)  =   (FORE(I,55)-FORE(I+8,47))
            WSERR(4,1)=WSERR(4,1)+WER(I,4)
            WSERR(4,2)=WSERR(4,2)+1
            WSERR(4,6)=WER(I,4)*WER(I,4)+WSERR(4,6)

            LWERR4(K,1)=LWERR4(K,1)+WER(I,4)
            LWERR4(K,2)=LWERR4(K,2)+1
            LWERR4(K,7)=WER(I,4)*WER(I,4)+LWERR4(K,7)

            ELSE
            TER(I,4)=-999
            WER(I,4)=-999
          ENDIF

C **** 72 HOUR FORECAST ERROR

        IF((FORE(I,20).EQ.FORE(I+12,20)).AND.(FORE(I,1.).GE.0.0)
     +.AND.(FORE(I+12,7).GE.0.0).AND.(FORE(I,39).GT.0.0).AND.
     +(FORE(I+12,27).GT.0.0))THEN

C ***** GREAT CIRCLE DISTANCE BETWEEN ACTUAL AND FORECASTED

        D1=(SIN(FORE(I,19)/PIR))
        D3=(SIN(FORE(I+12,7)/PIR))
        D2=(COS(FORE(I,19)/PIR))
        D4=(COS(FORE(I+12,7)/PIR))
        D6=(COS((FORE(I+12,27)-FORE(I,39))/PIR))

        IF((D1*D3+D2*D4*D6).GE.0.99999)THEN
          D7=0.0
         ELSE
          D7=ACOS(D1*D3+D2*D4*D6)
         ENDIF

        TER(I,5) = (D7*PIR)*60.0


         SUMERR(5,1)=SUMERR(5,1)+TER(I,5)
         SUMERR(5,2)=SUMERR(5,2)+1
         SUMERR(5,6)=TER(I,5)*TER(I,5)+SUMERR(5,6)

         LAERR5(K,1)=LAERR5(K,1)+TER(I,5)
         LAERR5(K,2)=LAERR5(K,2)+1
         LAERR5(K,7)=TER(I,5)*TER(I,5)+LAERR5(K,7)
```

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```
                WER(I,5) = (FORE(I,59)-FORE(I+12,47))
                WSERR(5,1)=WSERR(5,1)+WER(I,5)
                WSERR(5,2)=WSERR(5,2)+1
                WSERR(5,6)=WER(I,5)*WER(I,5)+WSERR(5,6)

                LWERR5(K,1)=LWERR5(K,1)+WER(I,5)
                LWERR5(K,2)=LWERR5(K,2)+1
                LWERR5(K,7)=WER(I,5)*WER(I,5)+LWERR5(K,7)

             ELSE
                TER(I,5)=-999
                WER(I,5)=-999
          ENDIF

600       CONTINUE

       DO 698 J=1,5,1

             SUMERR(J,3)= SUMERR(J,1)/SUMERR(J,2)

             SUMERR(J,4)=((SUMERR(J,6)-((SUMERR(J,3)**2)
      +*SUMERR(J,2))))/((SUMERR(J,2)-1))
             SUMERR(J,5)=SUMERR(J,4)**0.5

             WSERR(J,3)= WSERR(J,1)/WSERR(J,2)


             WSERR(J,4)=((WSERR(J,6)-((WSERR(J,3)**2)
      +*WSERR(J,2))))/((WSERR(J,2)-1))
             WSERR(J,5)=WSERR(J,4)**0.5

698       CONTINUE

       DO 810 J=1,7,1

             LAERR1(J,3)=LAERR1(J,1)/LAERR1(J,2)
             LAERR2(J,3)=LAERR2(J,1)/LAERR2(J,2)
             LAERR3(J,3)=LAERR3(J,1)/LAERR3(J,2)
             LAERR4(J,3)=LAERR4(J,1)/LAERR4(J,2)
             LAERR5(J,3)=LAERR5(J,1)/LAERR5(J,2)

      LAERR1(J,5)=(LAERR1(J,7)-(LAERR1(J,2)*(LAERR1(J,3)**2)))/
      +(LAERR1(J,2)-1)
      LAERR2(J,5)=(LAERR2(J,7)-(LAERR2(J,2)*(LAERR2(J,3)**2)))/
      +(LAERR2(J,2)-1)
      LAERR3(J,5)=(LAERR3(J,7)-(LAERR3(J,2)*(LAERR3(J,3)**2)))/
      +(LAERR3(J,2)-1)
      LAERR4(J,5)=(LAERR4(J,7)-(LAERR4(J,2)*(LAERR4(J,3)**2)))/
      +(LAERR4(J,2)-1)
      LAERR5(J,5)=(LAERR5(J,7)-(LAERR5(J,2)*(LAERR5(J,3)**2)))/
      +(LAERR5(J,2)-1)
```

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```fortran
      LAERR1(J,6)=LAERR1(J,5)**0.5
      LAERR2(J,6)=LAERR2(J,5)**0.5
      LAERR3(J,6)=LAERR3(J,5)**0.5
      LAERR4(J,6)=LAERR4(J,5)**0.5
      LAERR5(J,6)=LAERR5(J,5)**0.5

      LWERR1(J,3)=LWERR1(J,1)/LWERR1(J,2)
      LWERR2(J,3)=LWERR2(J,1)/LWERR2(J,2)
      LWERR3(J,3)=LWERR3(J,1)/LWERR3(J,2)
      LWERR4(J,3)=LWERR4(J,1)/LWERR4(J,2)
      LWERR5(J,3)=LWERR5(J,1)/LWERR5(J,2)

    LWERR1(J,5)=(LWERR1(J,7)-(LWERR1(J,2)*(LWERR1(J,3)**2)))/
   +(LWERR1(J,2)-1)
    LWERR2(J,5)=(LWERR2(J,7)-(LWERR2(J,2)*(LWERR2(J,3)**2)))/
   +(LWERR2(J,2)-1)
    LWERR3(J.5)=(LWERR3(J,7)-(LWERR3(J,2)*(LWERR3(J,3)**2)))/
   +(LWERR3(J,2)-1)
    LWERR4(J,5)=(LWERR4(J,7)-(LWERR4(J,2)*(LWERR4(J,3)**2)))/
   +(LWERR4(J,2)-1)
    LWERR5(J,5)=(LWERR5(J,7)-(LWERR5(J,2)*(LWERR5(J,3)**2)))/
   +(LWERR5(J,2)-1)

      LWERR1(J,6)=LWERR1(J,5)**0.5
      LWERR2(J,6)=LWERR2(J,5)**0.5
      LWERR3(J,6)=LWERR3(J,5)**0.5
      LWERR4(J,6)=LWERR4(J,5)**0.5
      LWERR5(J,6)=LWERR5(J,5)**0.5


810      CONTINUE


C*****************************************************************
C REPORTING STATISTICS ON THE FORECAST ERRORS
C*****************************************************************

      WRITE(*,700)
700   FORMAT('NAME OF FILE FOR OBS. FORECAST ERRORS?')
      READ(*,'(A)')NEWFL1
      OPEN(30,FILE=NEWFL1,STATUS='NEW')

      WRITE(*,710)
710   FORMAT('NAME OF FILE FOR ERROR SUMMARY STATISTICS?')
      READ(*,'(A)')NEWFL2
      OPEN(31,FILE=NEWFL2,STATUS='NEW')

      WRITE(*,711)
711   FORMAT('NAME OF FILE FOR STORING LAT FORECASTS?')
      READ(*,'(A)')NEWFL3
      OPEN(32,FILE=NEWFL3,STATUS='NEW')
```

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```
        WRITE(*,712)
712     FORMAT('NAME OF FILE FOR STORING LON FORECASTS?')
        READ(*,'(A)')NEWFL4
        OPEN(33,FILE=NEWFL4,STATUS='NEW')

        WRITE(*,713)
713     FORMAT('NAME OF FILE FOR STORING WS FORECASTS?')
        READ(*,'(A)')NEWFL5
        OPEN(34,FILE=NEWFL5,STATUS='NEW')

        WRITE(31,730)
        WRITE(31,731)
        WRITE(31,732)
        WRITE(31,731)

        WRITE(31,720) SUMERR(1,2), SUMERR(1,3), SUMERR(1,5),
+WSERR(1,3), WSERR(1,5)

        WRITE(31,731)

        WRITE(31,725) SUMERR(2,2), SUMERR(2,3), SUMERR(2,5),
+WSERR(2,3), WSERR(2,5)
        WRITE(31,731)

        WRITE(31,726) SUMERR(3,2), SUMERR(3,3), SUMERR(3,5),
+WSERR(3,3), WSERR(3,5)
        WRITE(31,731)

        WRITE(31,727) SUMERR(4,2), SUMERR(4,3), SUMERR(4,5),
+WSERR(4,3), WSERR(4,5)
        WRITE(31,731)

        WRITE(31,728) SUMERR(5,2), SUMERR(5,3), SUMERR(5,5),
+WSERR(5,3), WSERR(5,5)
        WRITE(31,731)

        DO 719 K=1,7,1
        WRITE(31,731)

        WRITE(31,729)K
        WRITE(31,731)
        WRITE(31,732)
        WRITE(31,731)

        WRITE(31,720) LAERR1(K,2), LAERR1(K,3), LAERR1(K,6),
+LWERR1(K,3), LWERR1(K,6)

        WRITE(31,731)

        WRITE(31,725) LAERR2(K,2), LAERR2(K,3), LAERR2(K,6),
+LWERR2(K,3), LWERR2(K,6)
```

```fortran
          WRITE(31,731)

              WRITE(31,726) LAERR3(K,2), LAERR3(K,3), LAERR3(K,6),
      +LWERR3(K,3), LWERR3(K,6)

           .  WRITE(31,731)

              WRITE(31,727) LAERR4(K,2), LAERR4(K,3), LAERR4(K,6),
      +LWERR4(K,3), LWERR4(K,6)

              WRITE(31,731)

              WRITE(31,728) LAERR5(K,2), LAERR5(K,3), LAERR5(K,6),
      +LWERR5(K,3), LWERR5(K,6)

              WRITE(31,731)
              WRITE(31,731)

 719          CONTINUE


 720          FORMAT(3X,'6HR',6X,F8,3X,F9.4,3X,F9.4,3X,Г9.4,3X,F9.4)
 725          FORMAT(3X,'12HR',5X,F8,3X,F9.4,3X,F9.4,3X,F9.4,3X,F9.4)
 726          FORMAT(3X,'24HR',5X,F8,3X,F9.4,3X,F9.4,3X,F9.4,3X,F9.4)
 727          FORMAT(3X,'48HR',5X,F8,3X,F9.4,3X,F9.4,3X,F9.4,3X,F9.4)
 728          FORMAT(3X,'72HR',5X,F8,3X,F9.4,3X,F9.4,3X,F9.4,3X,F9.4)
 729          FORMAT('*****FORECAST ERRORRS FOR LAT BAND=',I4)
 730          FORMAT('*****OVERALL FORECAST ERROR SUMMARY')
 731          FORMAT(' ')
 732          FORMAT('FORECAST',6X,'# OBS',7X,'MEAN',7X,'STDEV',
      +6X,'WS MEAN',6X,'WS STDEV')

C*****************************************************************
C REPORTING THE FORECASTS FOR LATITUDE, LONGITUDE, WIND SPEED
C AND THE GCD FORECAST ERROR FOR EACH PEPORT
C*****************************************************************


          DO 740 J=1,N,1

              WRITE(32,741)FORE(J,20),FORE(J, 7),FORE(J,8),
      +FORE(J,9),FORE(J,11),FORE(J,15),FORE(J,19)

              WRITE(33,741)FORE(J,20),FORE(J, 27),FORE(J,28),
      +FORE(J,29),FORE(J,31),FORE(J,35),FORE(J,39)

              WRITE(34,741)FORE(J,20),FORE(J, 47),FORE(J,48),
      +FORE(J,49),FORE(J,51),FORE(J,55),FORE(J,59)

 741          FORMAT(' ',7(F8.2,1X))
 740       CONTINUE
```

```
      DO 750 J=1,N,1

          WRITE(30,751)FORE(J,20), TER(J, 1),
     +       TER(J, 2), TER(J, 3), TER(J, 4), TER(J, 5)

751       FORMAT(' ',6(F8.2,1X))
750    CONTINUE


       END

C***** END OF FORECASTING PROGRAM
```

Appendix I. Sample Hurricane Track Data Base

This is a sample of the best track data matrix used in this research, where each row represents a 6 hour report. Best tracks are constructed in a careful post-storm analysis that combines position data from all available sources. Some subjective smoothing is employed to plot the best track.

Column 1: Report storm ID (the storm number and the year). For example, the first storm of 1986 would have an ID of 0186.

Column 2: Report DATE (mmdd). For example, if the report was taken on June 16th, the report DATE would be 0616.

Column 3: Report TIME in Zulu. For example, if the report was taken at midnight Zulu time, the report TIME would be 0000.

Column 4: Report latitude (LAT) in north degrees. For example, if at the report the eye of the hurricane had a latitude of 45.8 north degrees, the report LAT would be 458

Column 5: Report latitude (LON) in west degrees. For example, if at the report the eye of the hurricane had a longitude of 88.6 west degrees, the report LON would be 886.

Column 6: Report maximum sustained wind speed (WS) in miles per hour. For example, if at the report the hurricane had a maximum sustained wind speed of 130 miles per hour, the report WS would be 130.

A sample of the data:

```
0186  0608  00 352  739  45
0186  0608  06 363  727  45
0186  0608  12 379  710  40
0186  0608  18 396  689  35
0286  0623  18 256  872  25
0286  0624  00 257  878  25
0286  0624  06 260  884  25
0286  0624  12 264  889  30
0286  0624  18 266  895  40
0286  0625  00 267  903  45
0286  0625  06 268  910  50
0286  0625  12 272  917  55
0286  0625  18 277  922  65
```

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Vita

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